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Bergen, 8 October 2015

Barcelona Supercomputing Center
Centro Nacional de Supercomputación

EXCELENCIA SEVERO OCHOA

Climate prediction in a user-driven context

Francisco J. Doblas-Reyes
BSC Earth Sciences Department

SPECS
Seasonal-to-decadal climate Prediction for the improvement of European Climate Services

iCrea

BSC Earth Sciences Department

Barcelona Supercomputing Center
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EXCELENCIA SEVERO OCHOA

What

Environmental forecasting

Why

Our strength …
… research …
… operations …
… services …
… high resolution …

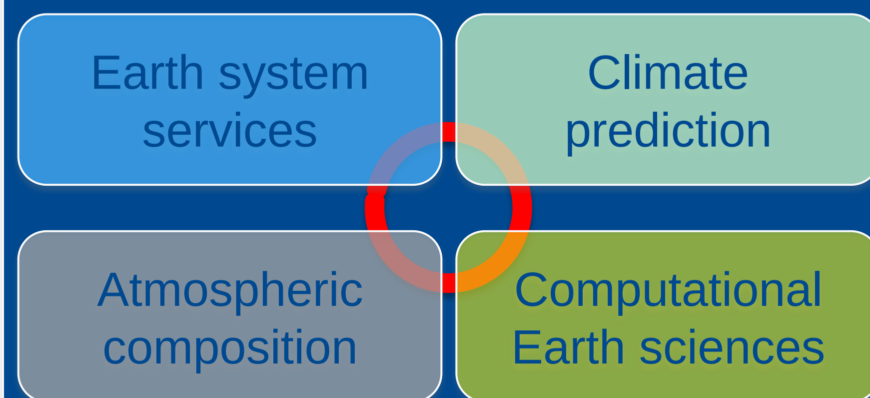
How

Develop a capability to model air quality processes from urban to global and the impacts on weather, health and ecosystems

Implement climate prediction system for subseasonal-to-decadal climate prediction

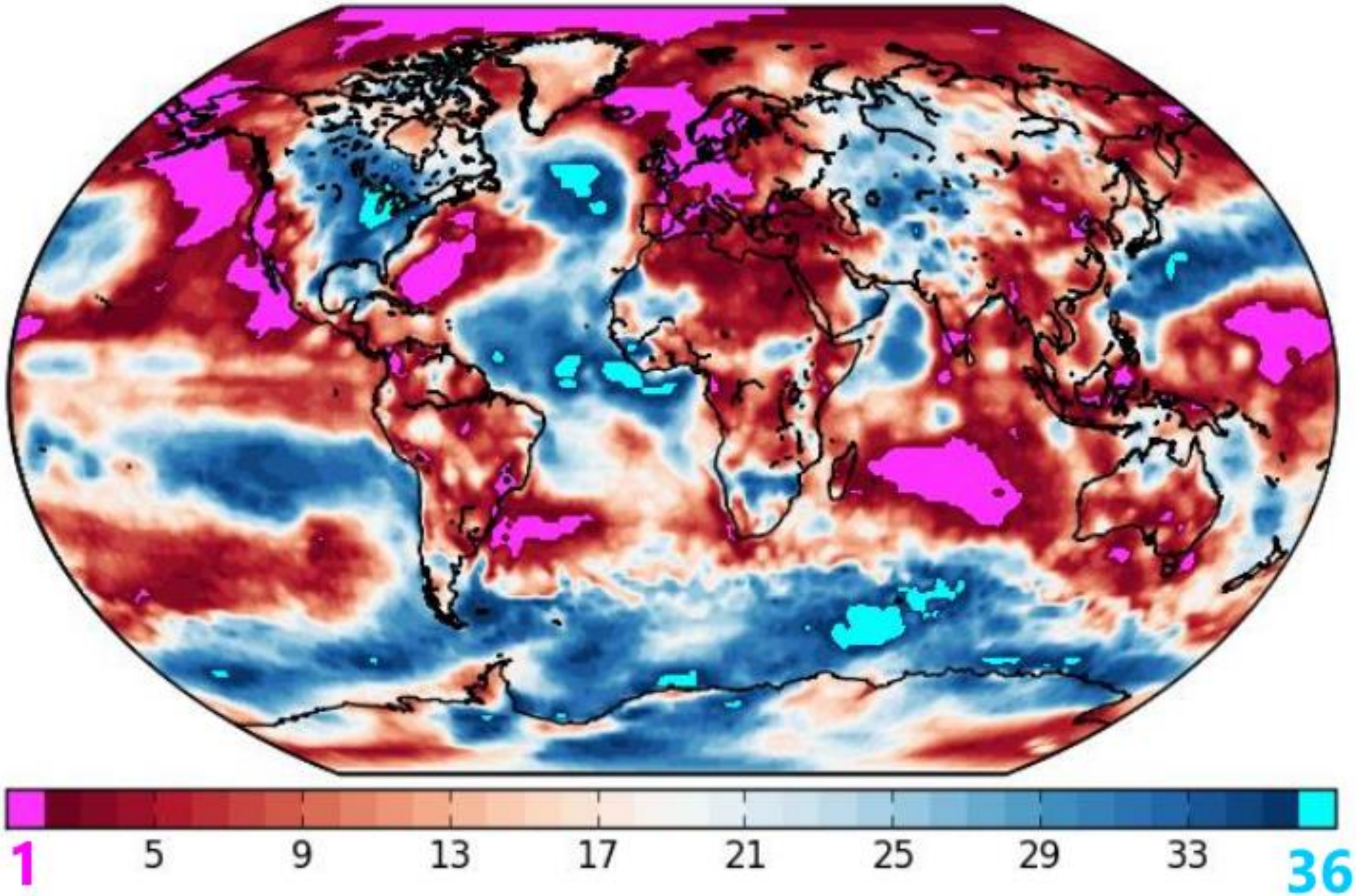
Develop user-oriented services that favour both technology transfer and adaptation

Use cutting-edge HPC and Big Data technologies for the efficiency and user-friendliness of Earth system models



2014, a special year

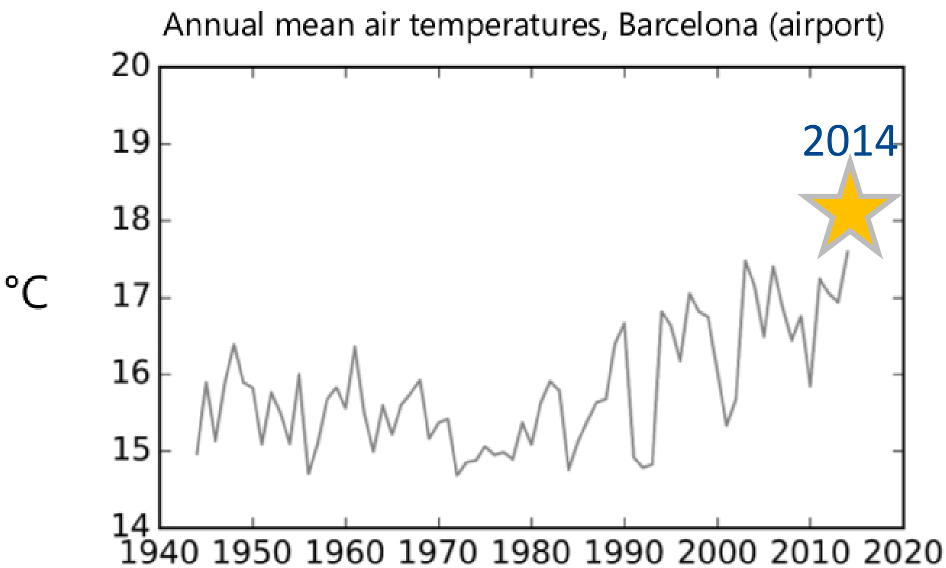
Rank of the 2014 annual mean temperature over the last 36 years from ERA Interim.

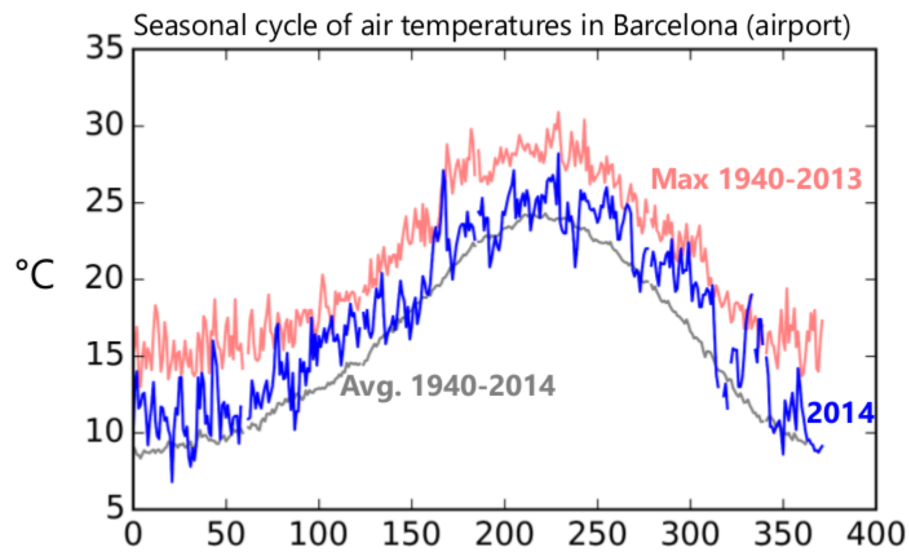


François Massonnet (IC3)

2014, a special year

Temperatures in Barcelona airport from the ECAD dataset.

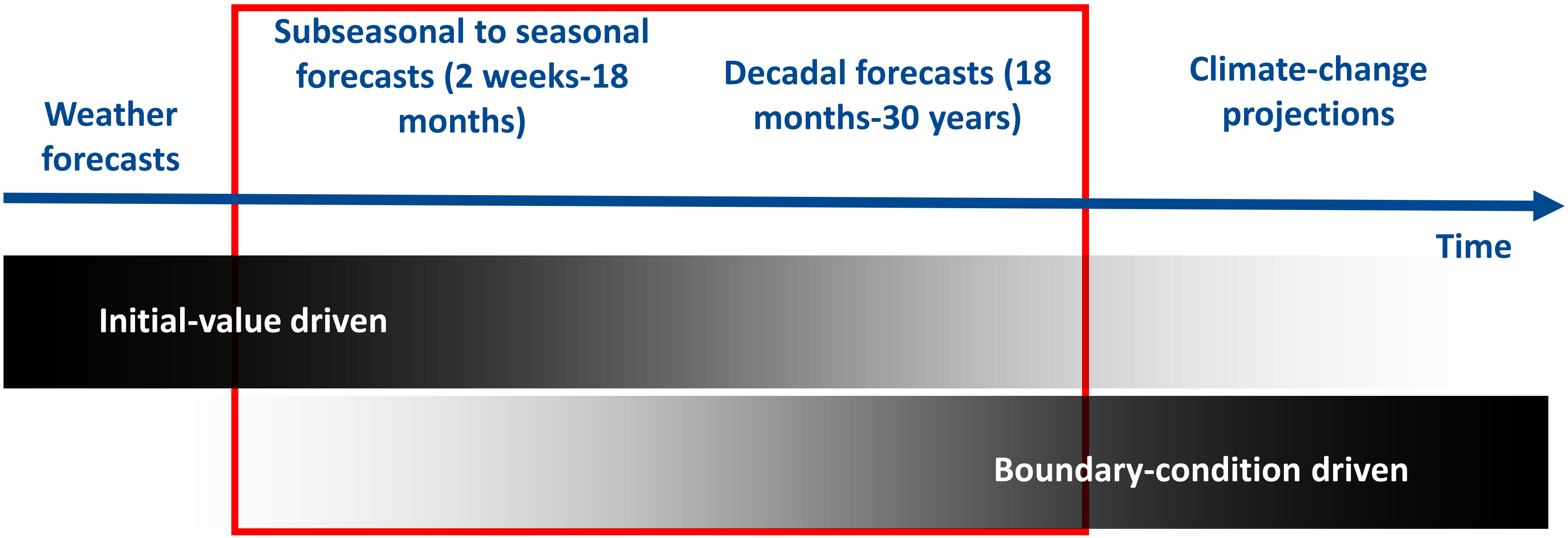




François Massonnet (IC3)

Climate prediction time scales

Progression from initial-value problems with weather forecasting at one end and multi-decadal to century projections as a forced boundary condition problem at the other, with climate prediction (sub-seasonal, seasonal and decadal) in the middle. Prediction involves initialization and systematic comparison with a simultaneous reference.



Adapted from Meehl et al. (2009)

Initialising climate predictions

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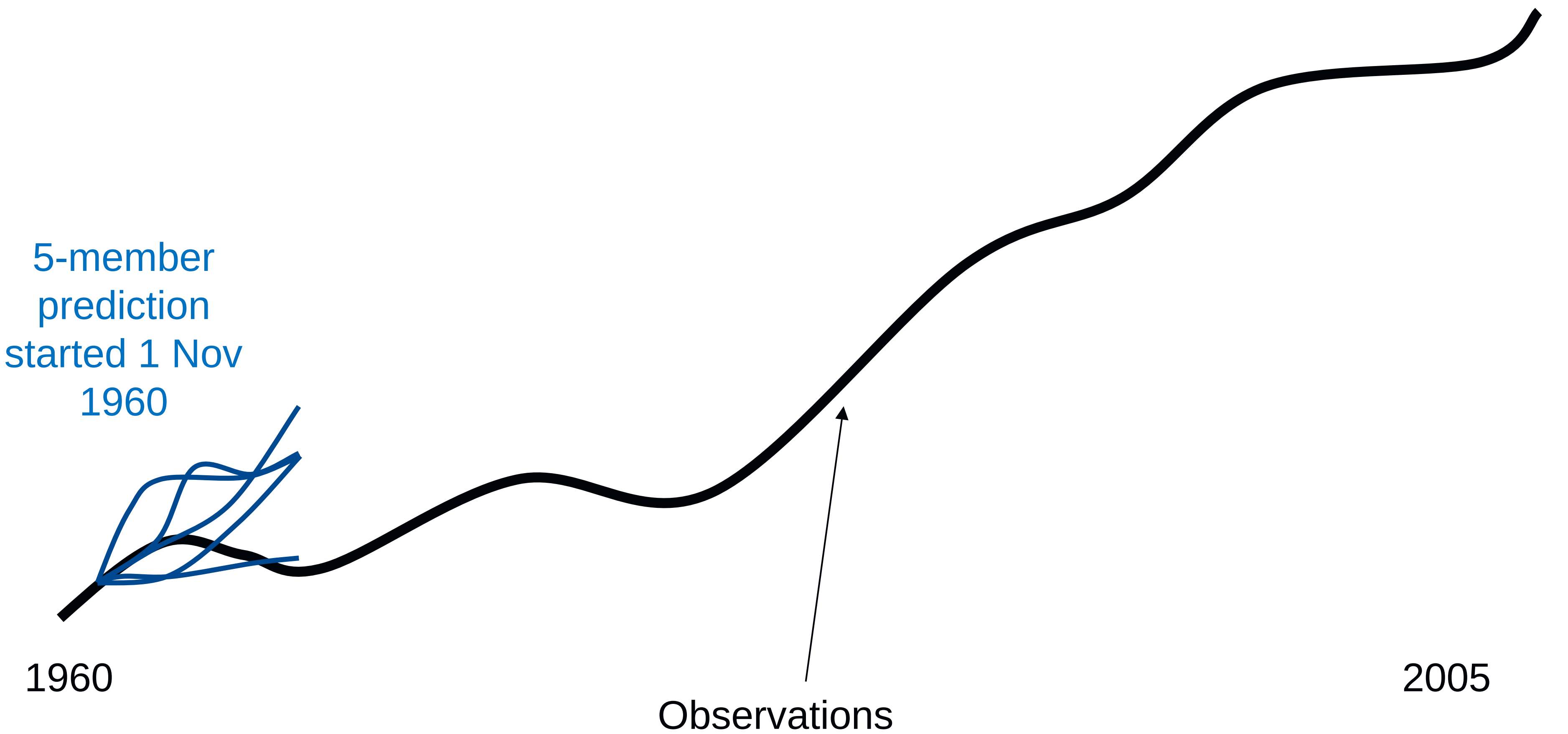
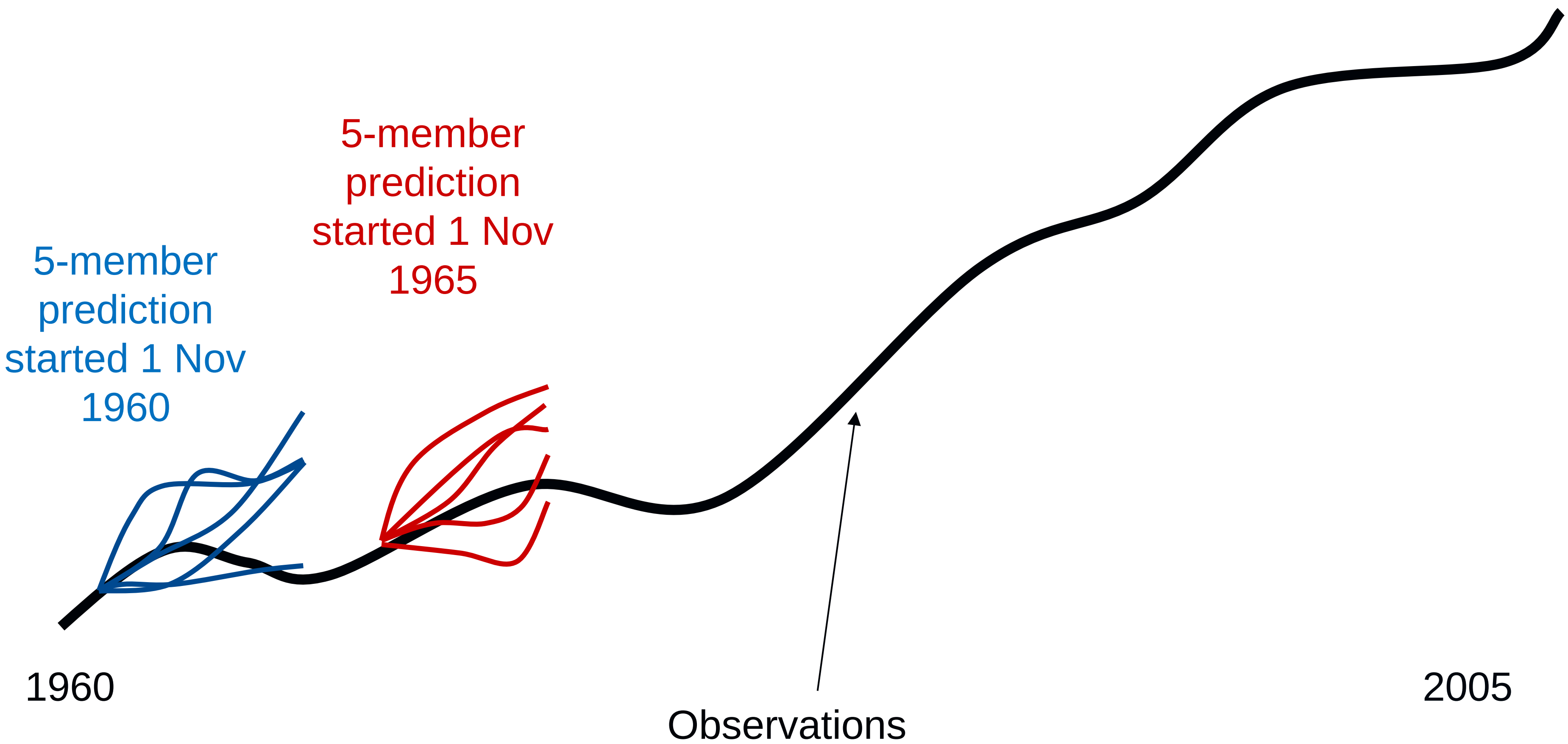
- Why initialising a climate model? To address the internal variability uncertainty source and make a skilful forecast, one of the requirements is an accurate knowledge of the initial state of the system.
- Steps to initialise an ensemble climate forecast system:
  - make the most of the available observations to rebuild the best estimate of the system state (reanalysis).
  - transfer such information to the model avoiding imbalances, i.e. initialise the climate prediction system
  - run the ensemble with initial perturbations to account for the initial-state uncertainty

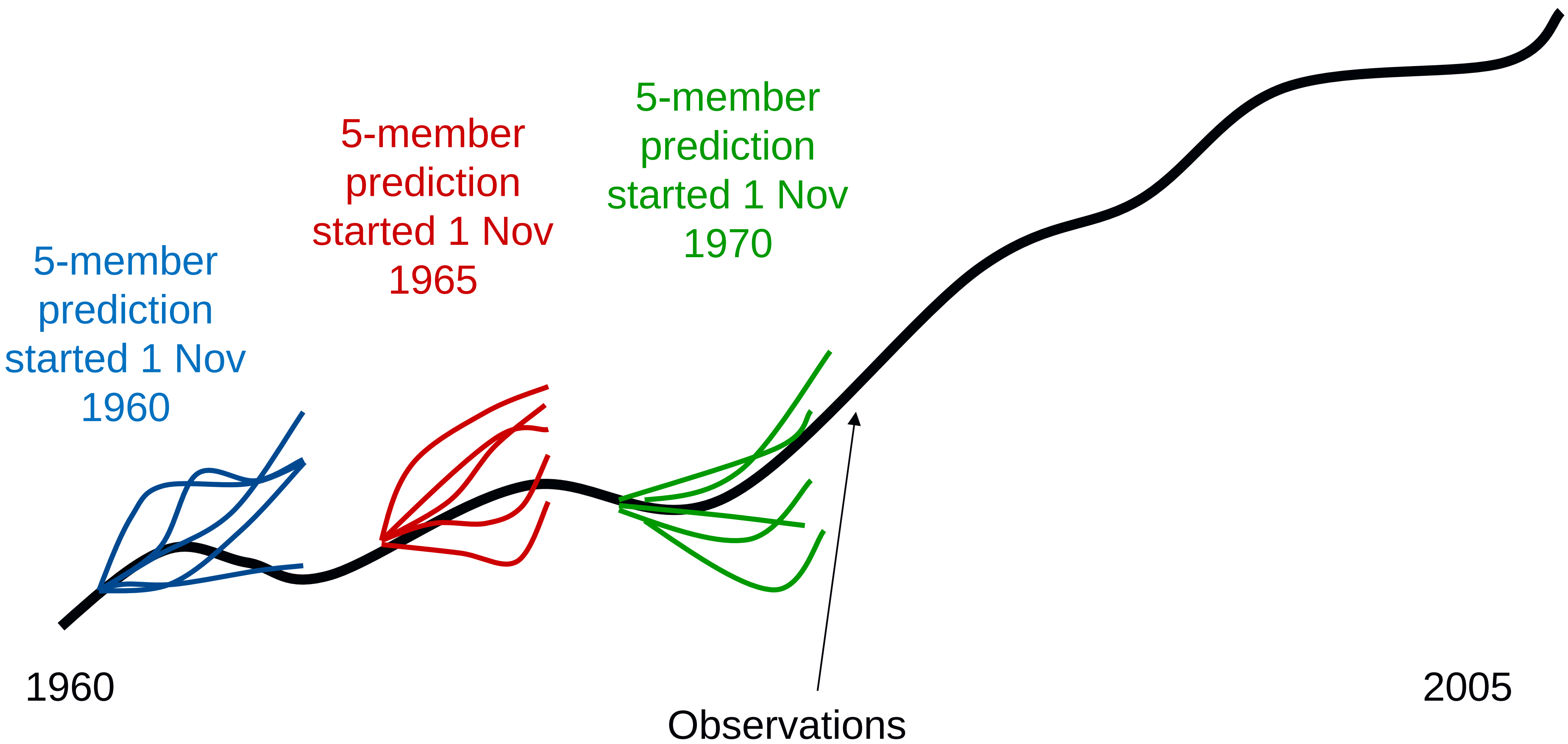
Climate prediction experiments



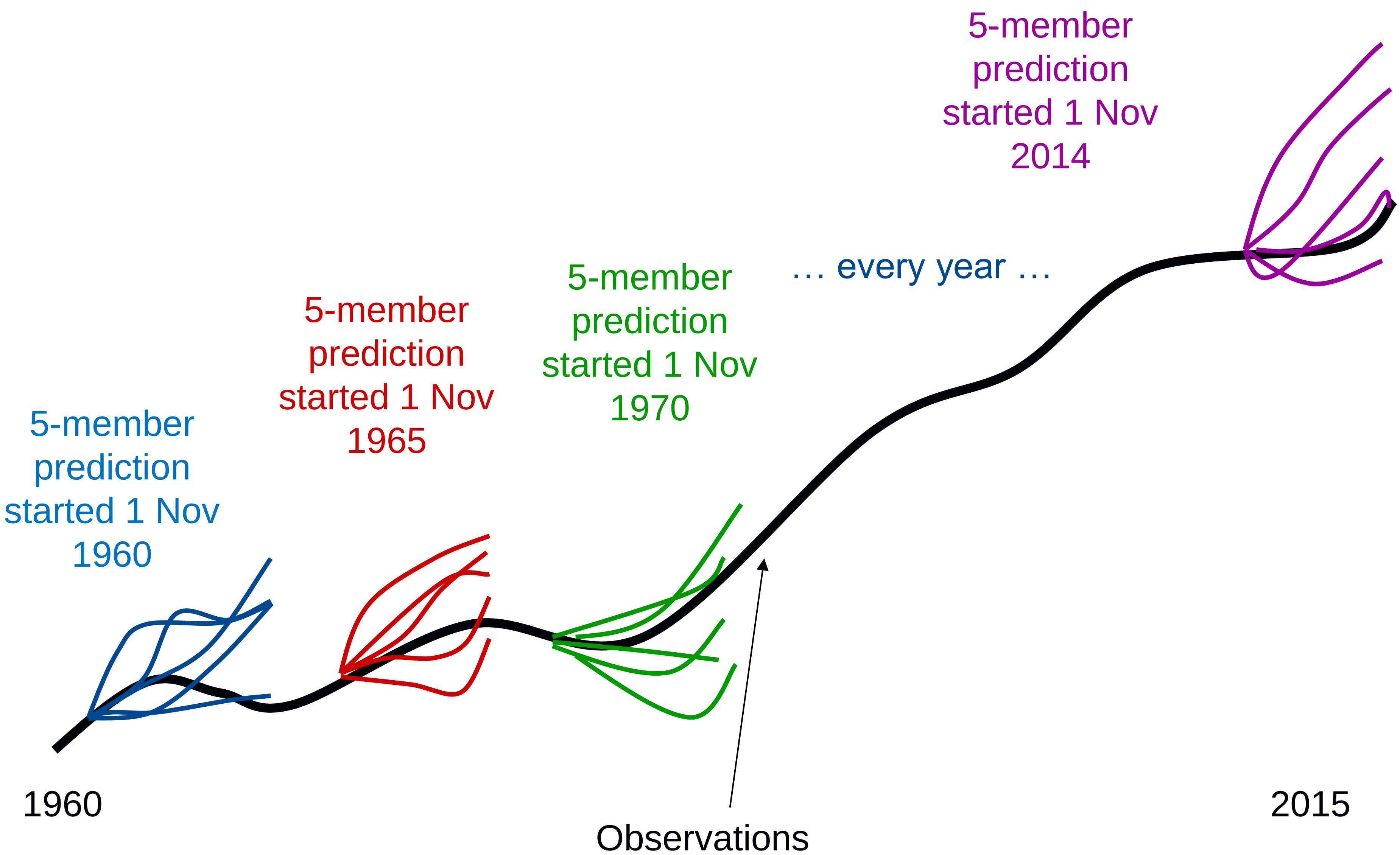
Climate prediction experiments



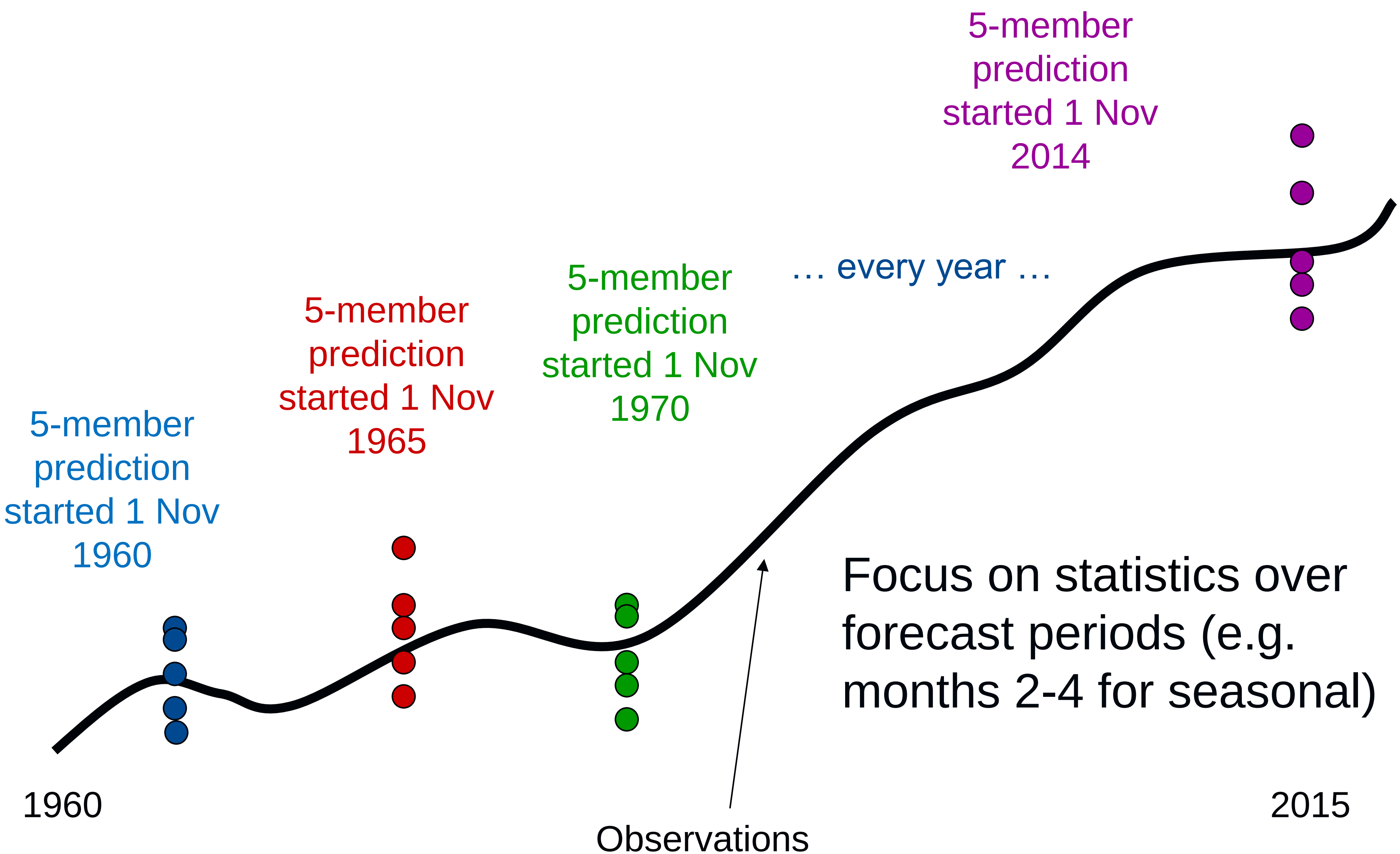
Climate prediction experiments



Climate prediction experiments



Climate prediction experiments

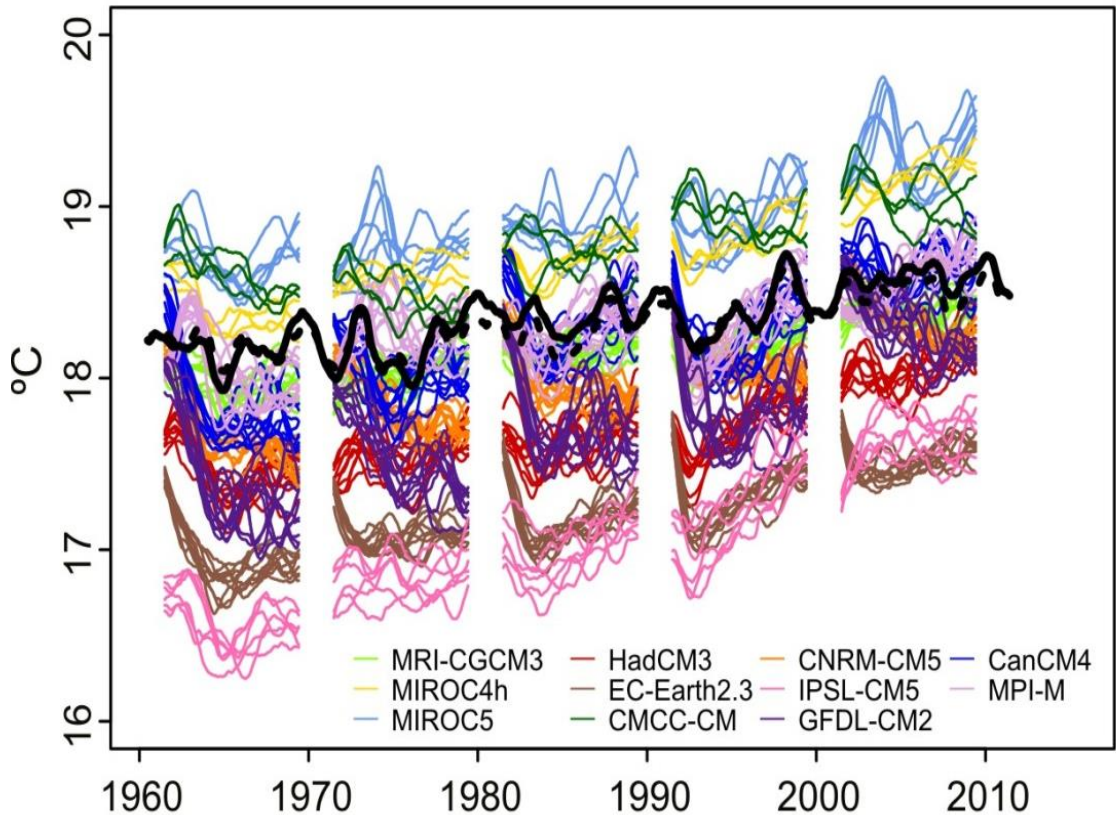


Focus on statistics over forecast periods (e.g. months 2-4 for seasonal)

Systematic errors in climate prediction

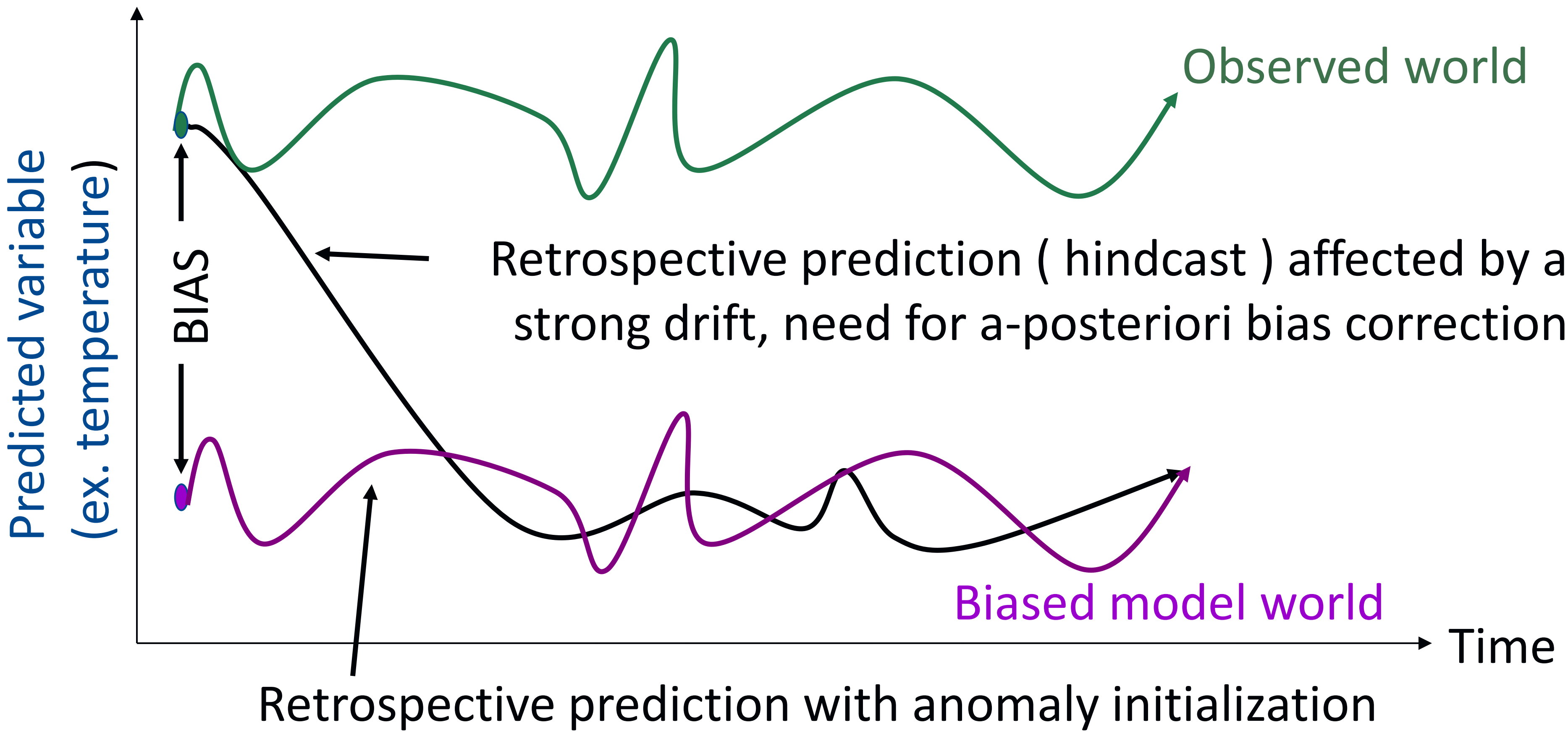
Global mean near-surface air temperature over the ocean (one-year running mean applied) from CMIP5 hindcasts. Each system is shown with a different colour. NCEP and ERA40/Int used as reference.

Shock and drift is the norm.



IPCC AR5 WGI (2013)

The climate prediction drift issue

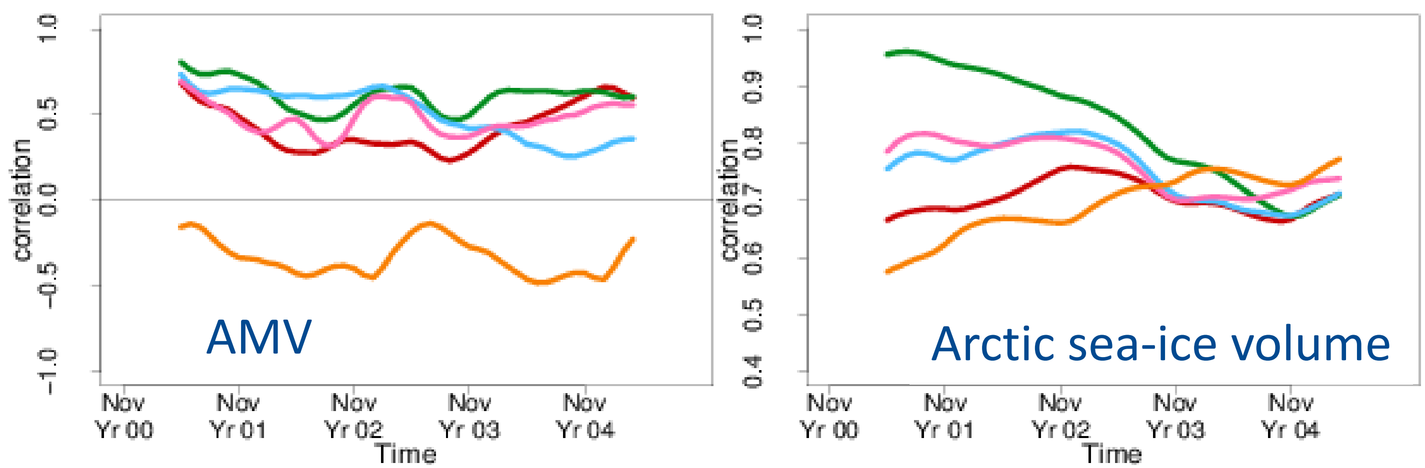


Initialization approaches

Assessment of full-field (red), anomaly in the ocean (blue), weighted anomaly in the ocean and the sea ice, with initialisation of temperature and density instead of the usual temperature and salinity (green), and a weighted anomaly nudging in the ocean (pink).

Decadal prediction experiments run with EC-Earth2.3. Comparison with historical ensemble simulation (orange). 5 ensemble members, one start date every 2 years.

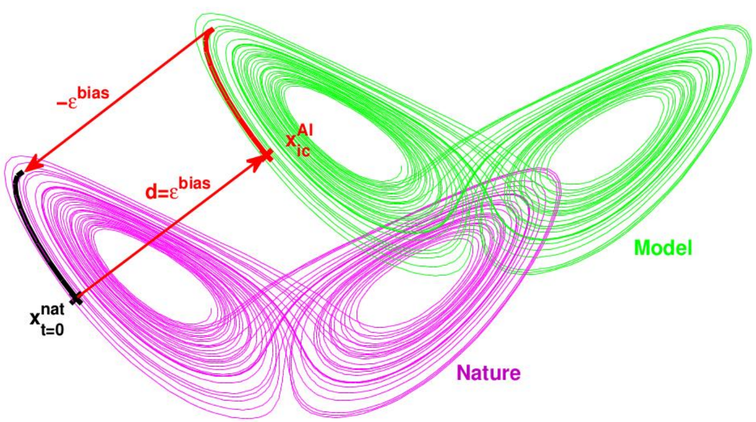
Reference data: ERSST data for AMO and SST, sea-ice reconstruction from Guemas et al. 2013 for sea-ice area and volume.



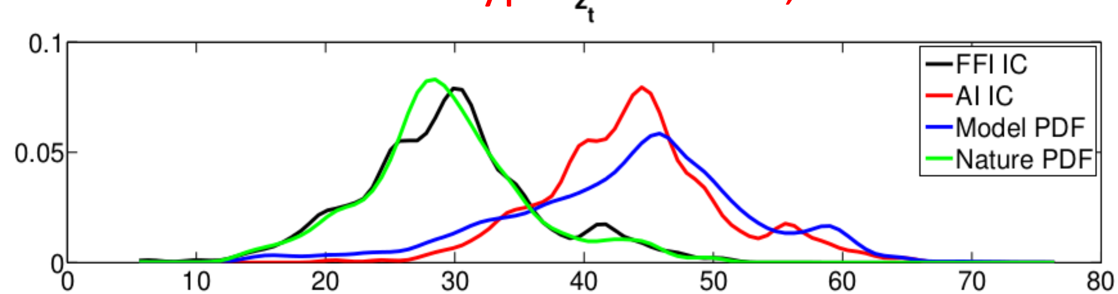
Volpi et al. (2015, Clim. Dyn.)

Initialization: back to simple models

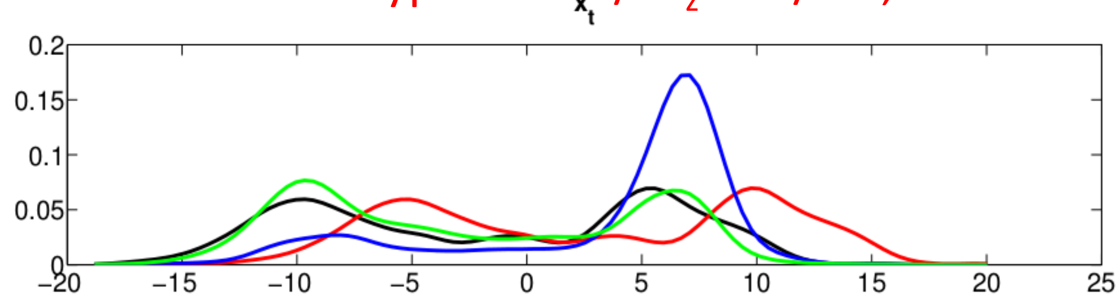
PDFs of initial conditions (black and red) and of the model and "nature" climatologies (blue and green) for the Peña and Kalnay model with three compartments (ocean, tropical atmosphere and extra-tropical atmosphere).



Model error "type #2" r^m=42, AI better



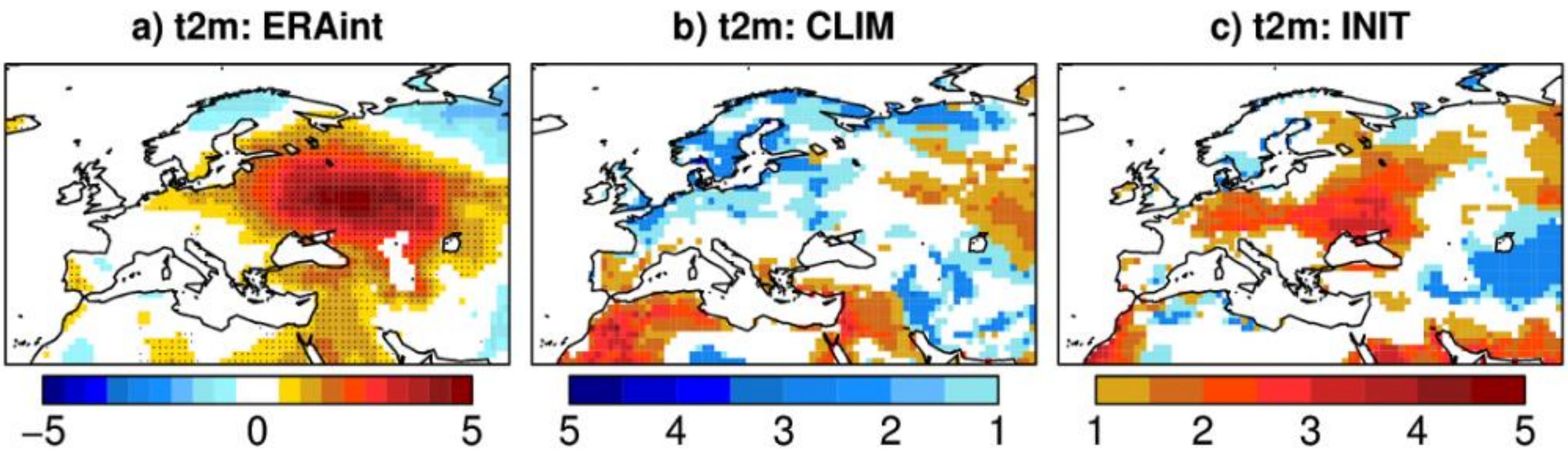
Model error "type #1" c^m/c^m_z=0.8/0.9, FFI better



Weber et al. (2015, MWR)

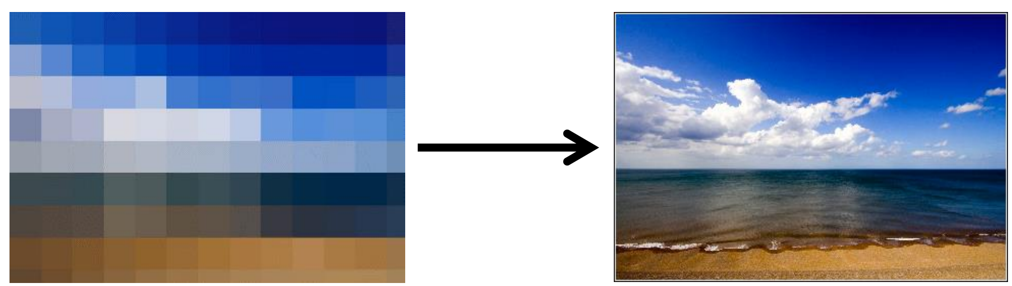
Improving temperature forecasts

JJA near-surface temperature anomalies in 2010 from ERAInt (left) and odds ratio from experiments with a climatological (centre) and a realistic (right) land-surface initialisation. Results for EC-Earth2.3 started in May with initial conditions from ERAInt, ORAS4 and a sea-ice reconstruction over 1979-2010.



Similar results found for EC-Earth3 and high resolution (25 km).

Prodhomme et al. (2015, Clim. Dyn.)



Predicting “extremes” within the month

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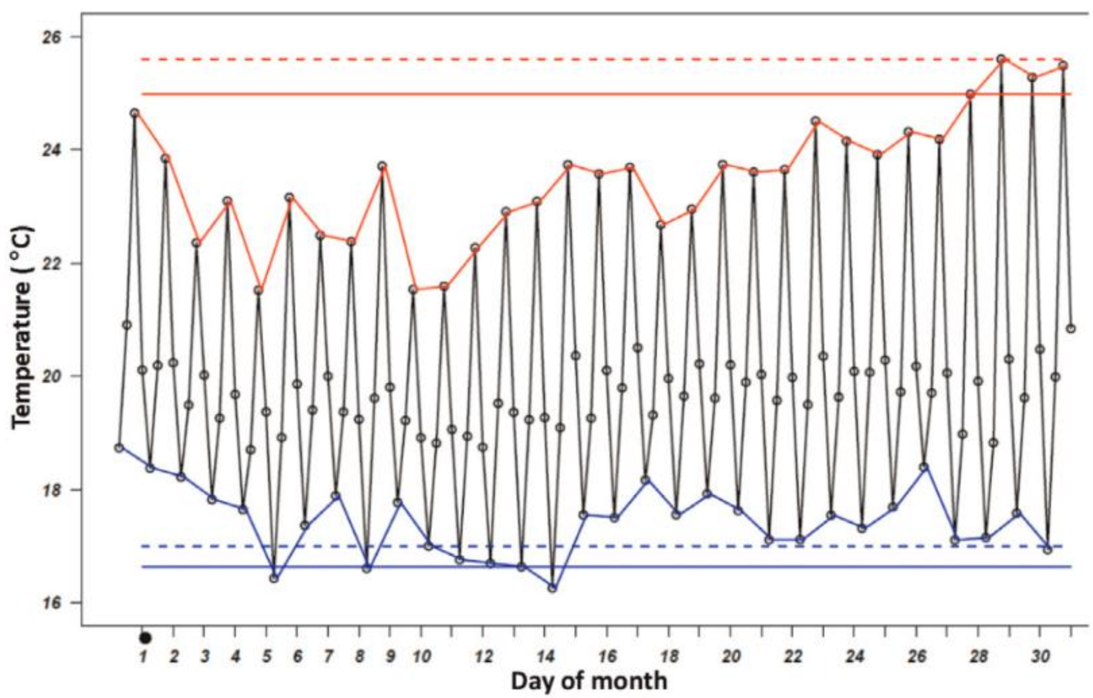
ERAInt six-hourly temperature for an arbitrary month and point. Red lines indicate the daily maximum temperature and blue lines the daily minimum temperature. The dashed horizontal lines indicate the climatological 90th and 10th percentiles of daily variability, while the solid horizontal lines indicate the month’s 90th and 10th percentiles.

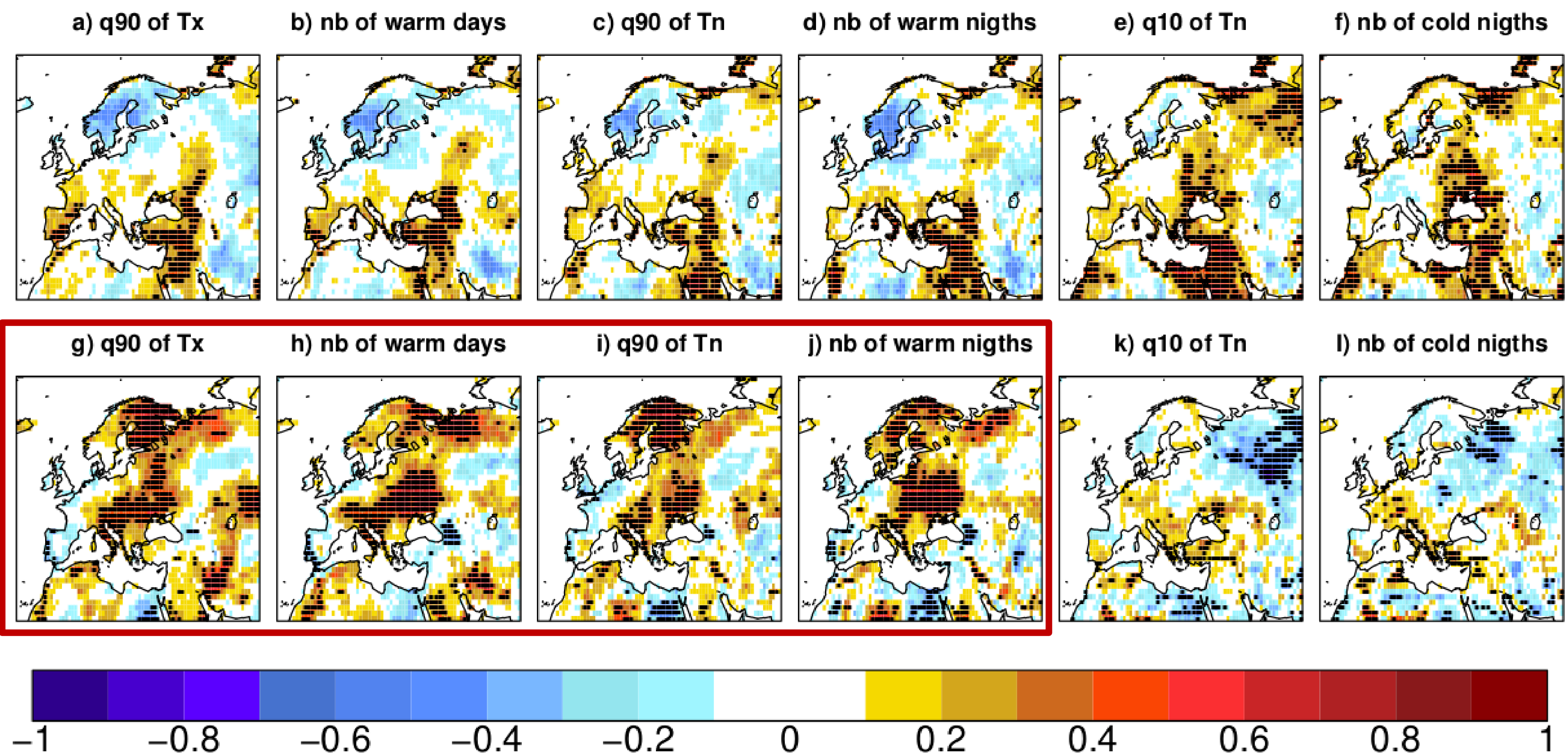
This month has 7 cold and one warm days, while the monthly 90th and 10th percentiles are both lower than the long-term value.

Peppler et al. (2015, WCE)



Improving temperature forecasts

JJA near-surface temperature correlation of the ensemble mean from experiments with a climatological (top) and difference with one with realistic (bottom) land-surface initialisation. Results for EC-Earth2.3 started in May over 1979-2010.

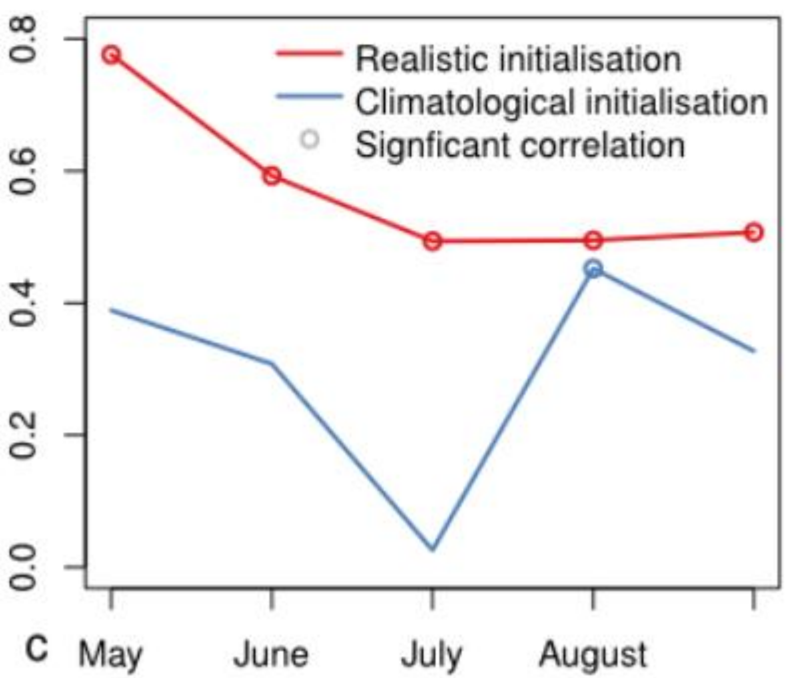


Prodhomme et al. (2015, Clim. Dyn.)

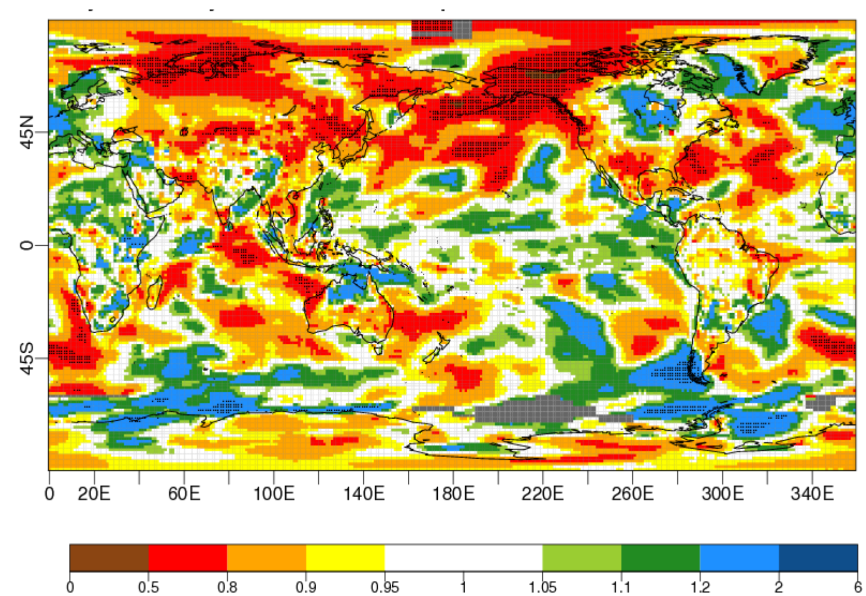
Improving Arctic forecasts

Predictions with EC-Earth started every May (left) and November (right) over 1993-2009 (let) and 1979-2010 (right) with ERAInt and ORAS4 initial conditions, and internal sea-ice reconstruction. Two sets, one initialised with realistic and another one with climatological sea-ice initial conditions.

Arctic sea-ice area



Ratio RMSE Init/Clim hindcasts 2-metre temperature (months 2-4)

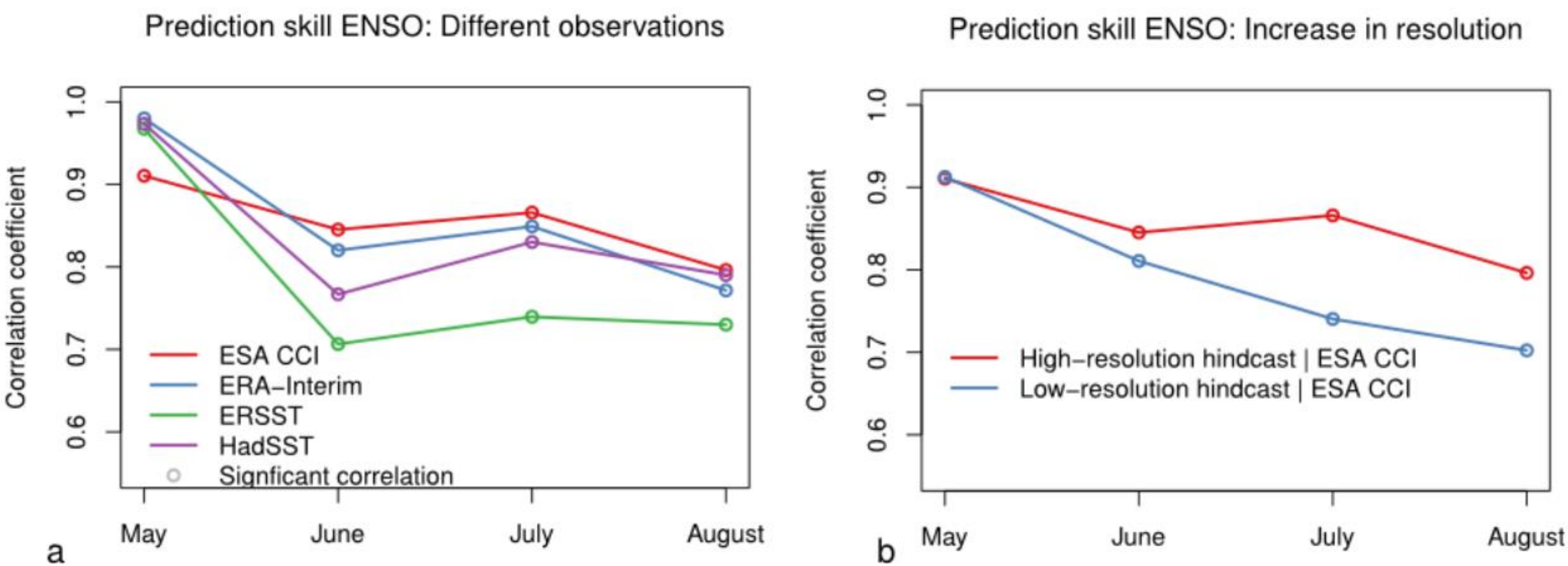


Guemas et al. (2015, GRL)

Bellprat et al. (2015, IC3 Tech Note)

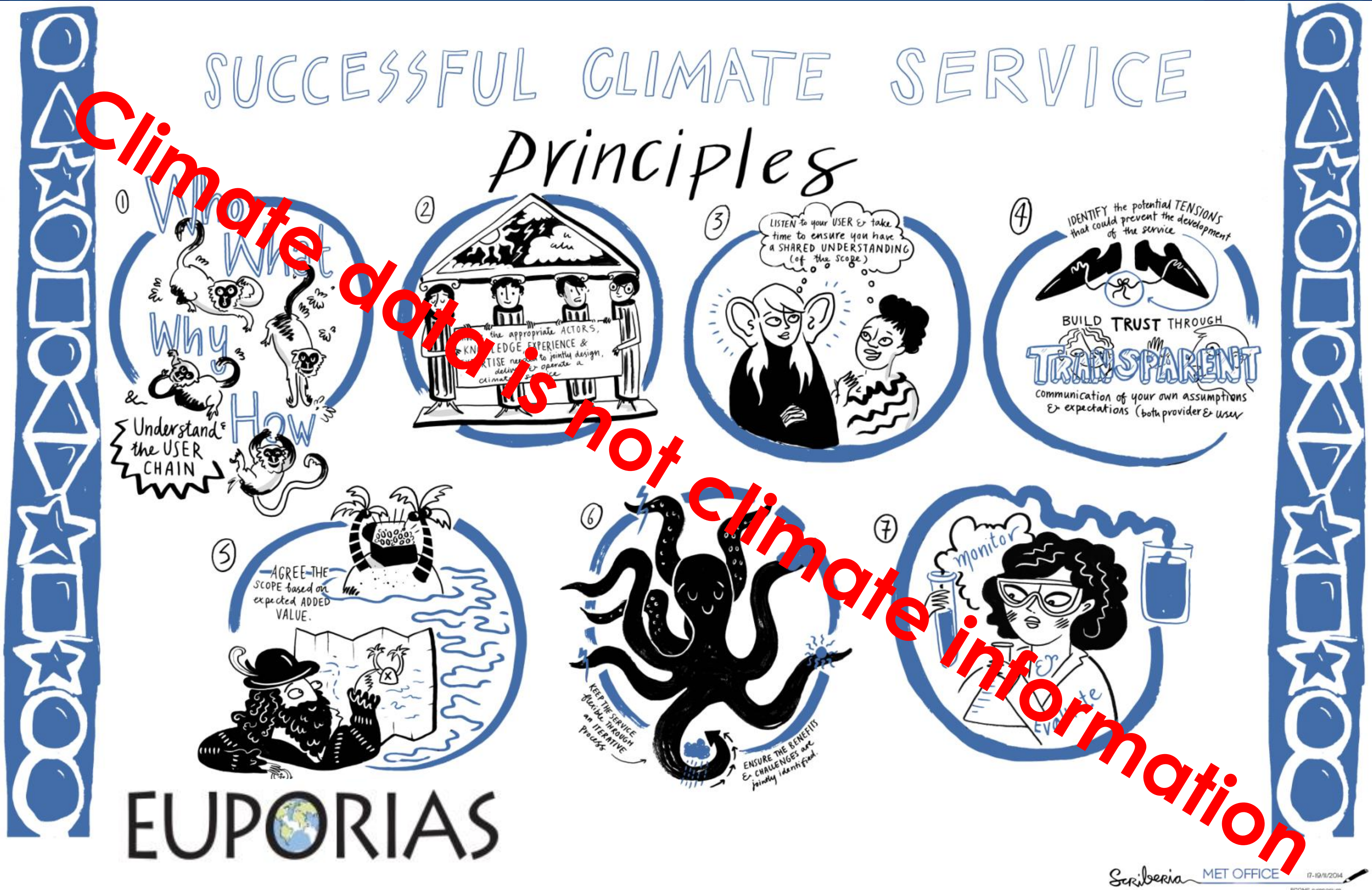
Observational uncertainty

Predictions with EC-Earth3 started every May over 1993-2009 with ERAInt and GLORYS2v1 initial conditions, and internal sea-ice reconstruction.



Bellprat et al. (2015, IC3 Tech Note)

Service-driven climate research



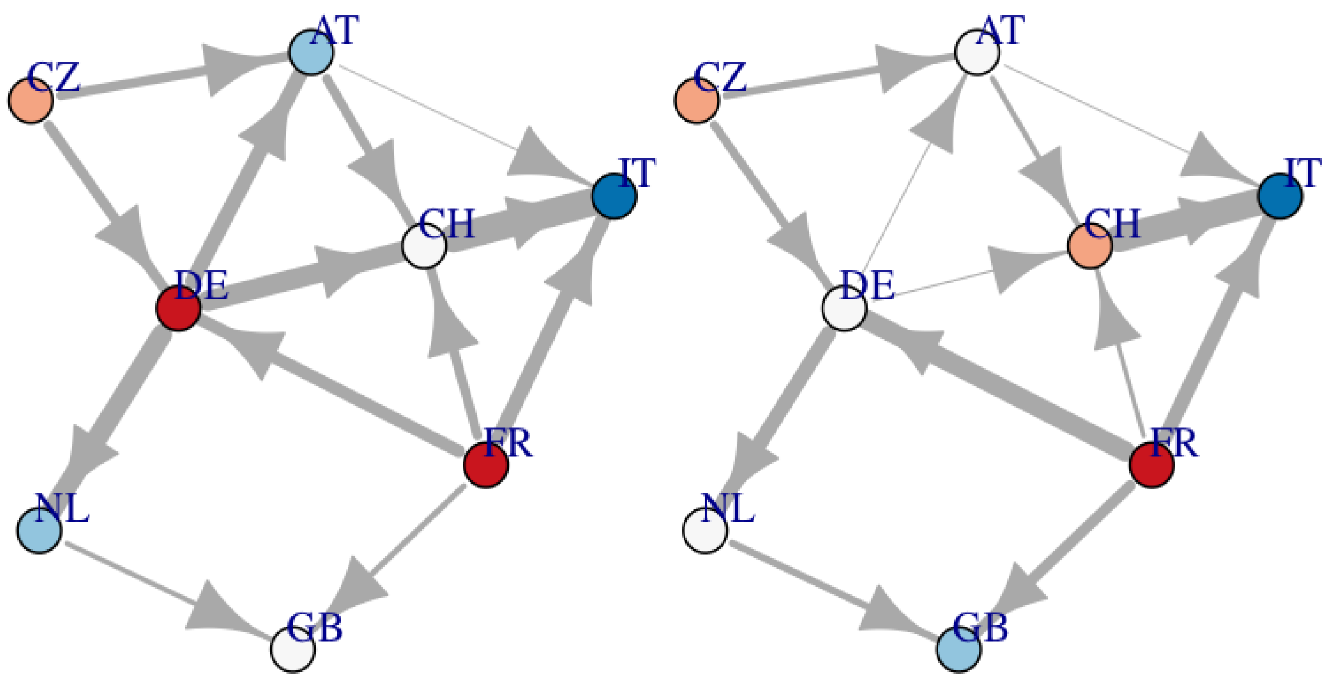
Climate data is not climate information

Ethical Framework for Climate Services four core elements: integrity, transparency, humility and collaboration.

Temperature forecasts for energy

European electricity flows for Jan-Feb (left) and June-July (right). Red nodes are the main exporters and blue the main importers. For clarity only the eight countries with the highest exchange are shown.

Data from ENTSO-E (2003-2014).



M. De Felice (ENEA)

Temperature forecasts for energy

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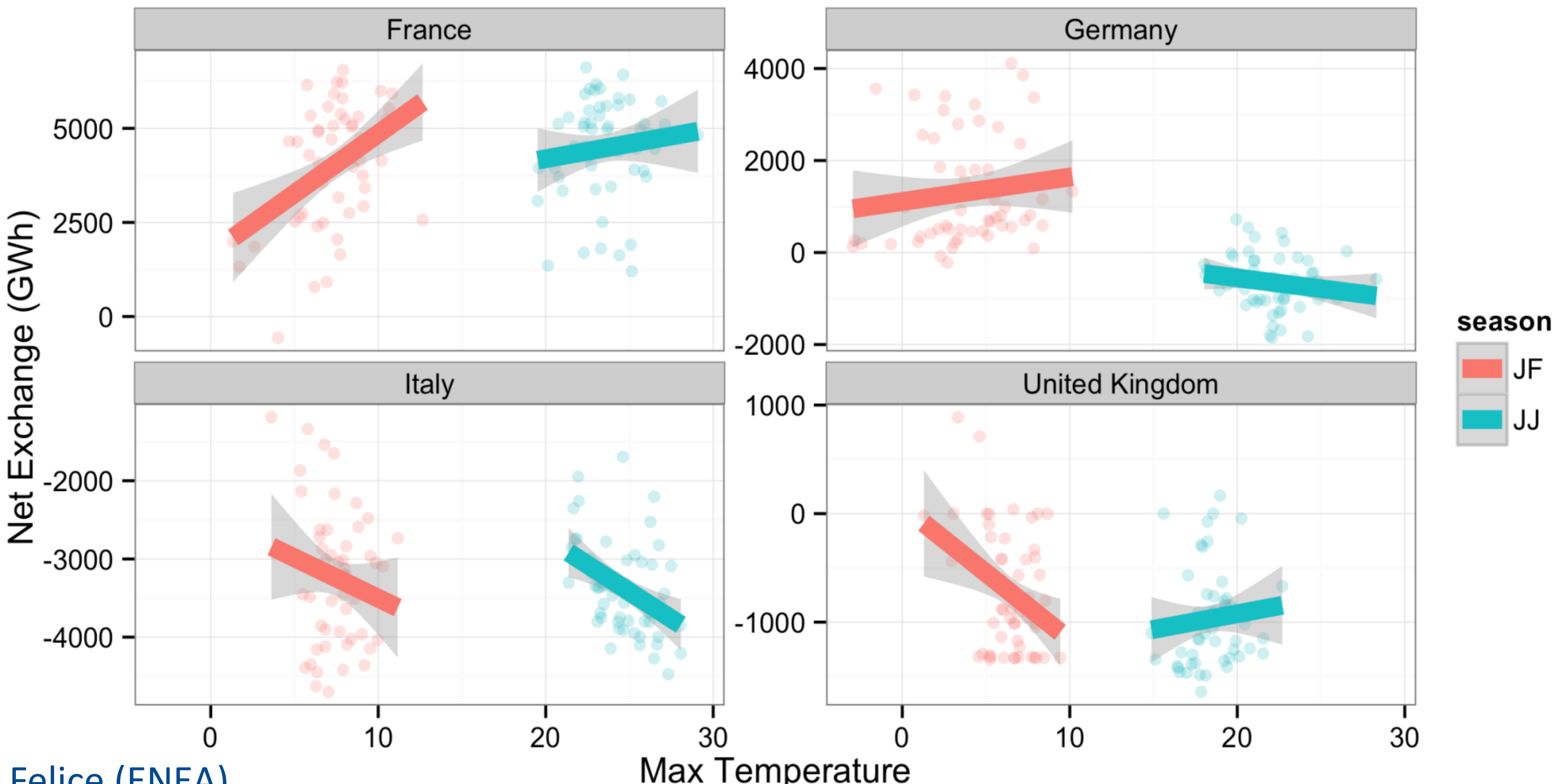
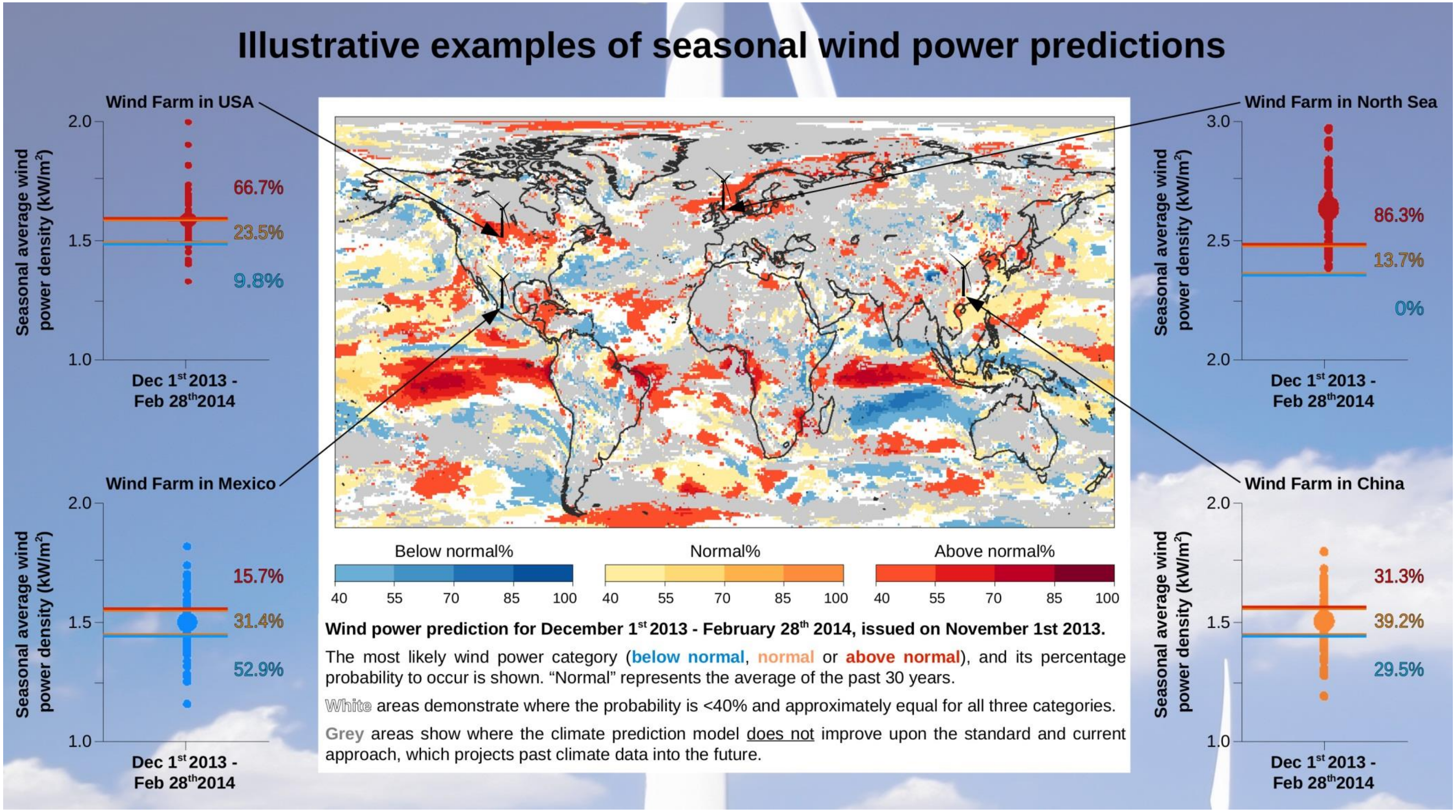
Weather and climate affect exchanges via electricity demand (heating or cooling, from the customer point of view) and RE production.

Data from ENTSO-E (2003-2014).



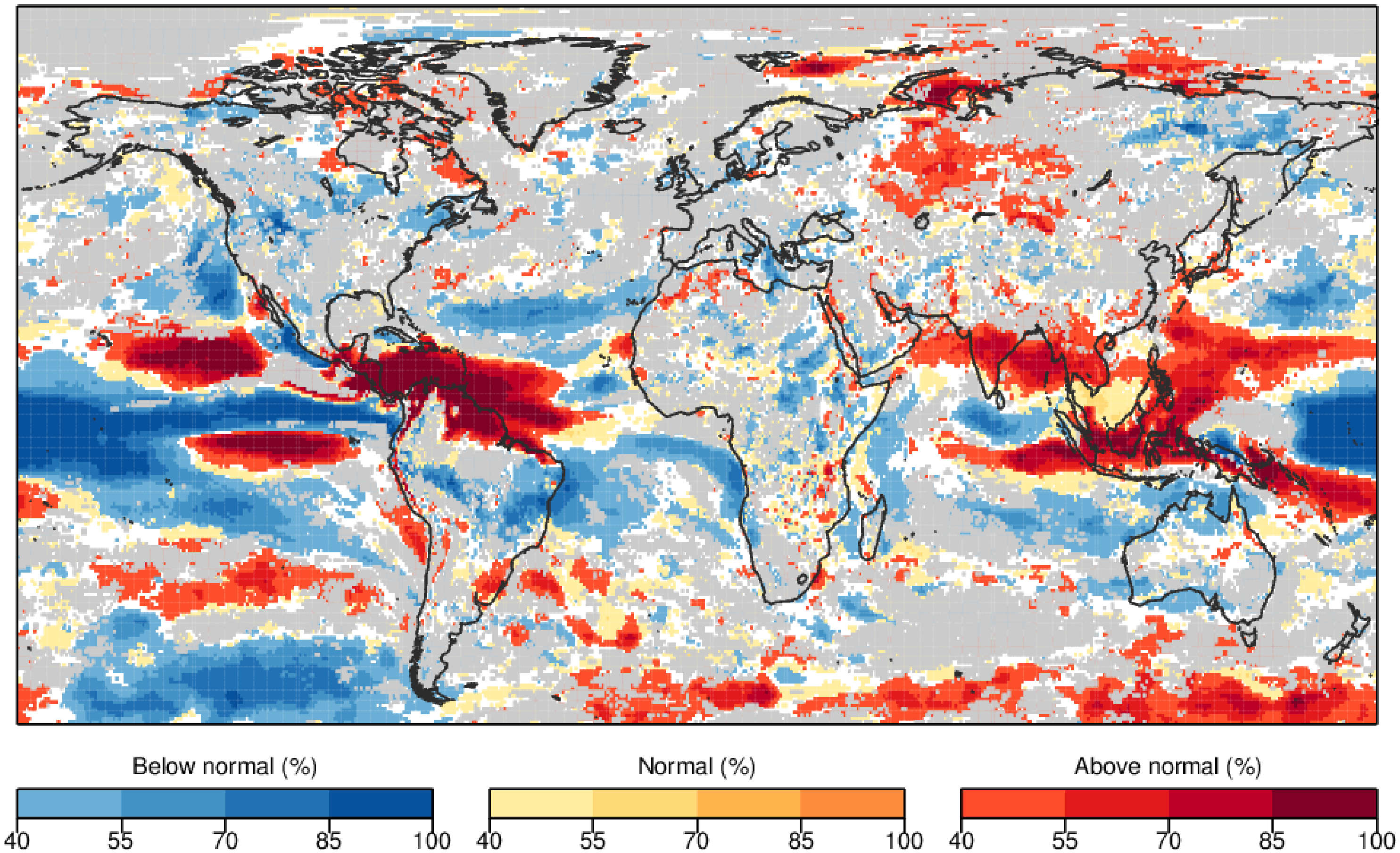
M. De Felice (ENEA)

Climate data for wind energy



Forecasts for wind energy

Predictions of 10-metre wind speed for the above normal category (using tercile thresholds) from ECMWF S4 for JJA 2015.

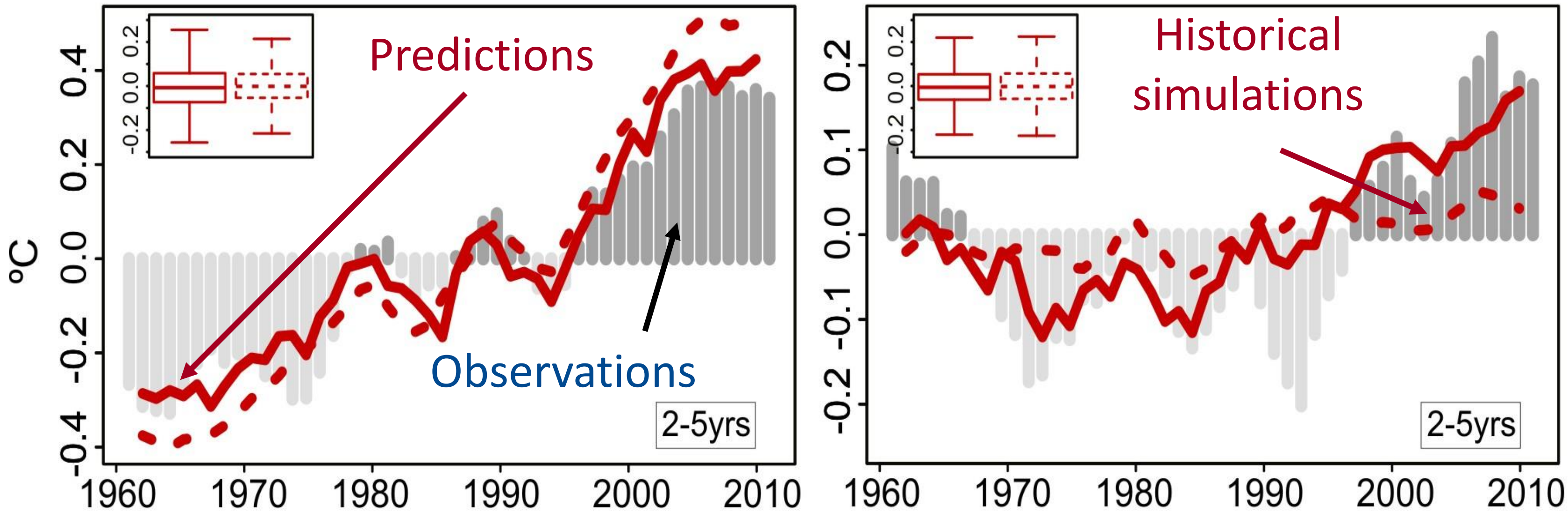


V. Torralba (IC3)

Decadal climate prediction

Global mean surface air temperature (GMST)

Atlantic multidecadal variability (AMV)

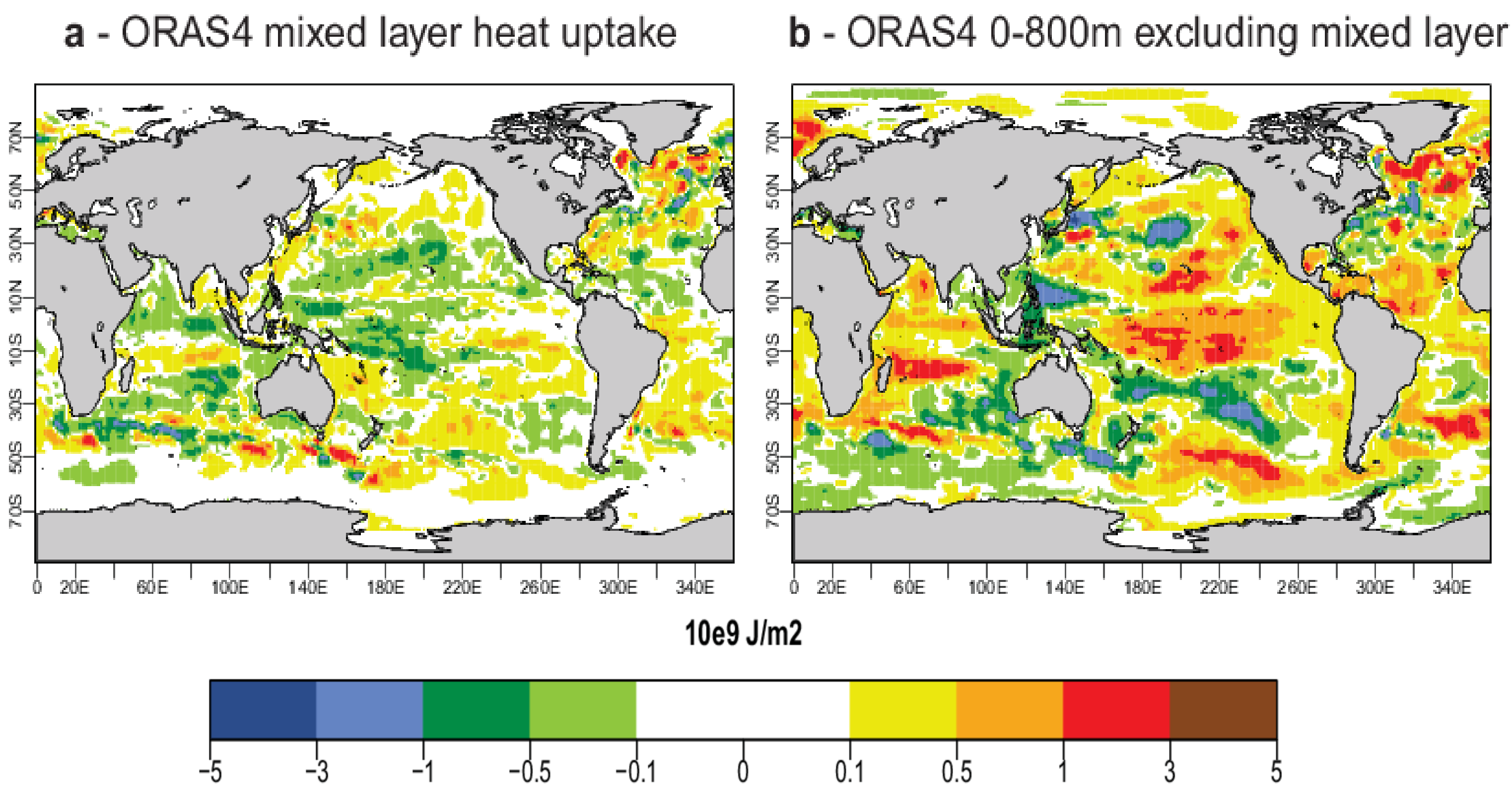


Initialised simulations reproduce the temperature trends and the AMV variability and suggest that initialization corrects the forced model response and phases in internal variability.

Doblas-Reyes et al. (2013, Nat. Comms.)

Decadal climate prediction

Ocean heat uptake computed as the average of the differences over the periods (2002-2005)-(1998-2001) from the ORAS4 ocean reanalysis.



Guemas et al. (2013, NCC)

Decadal climate prediction

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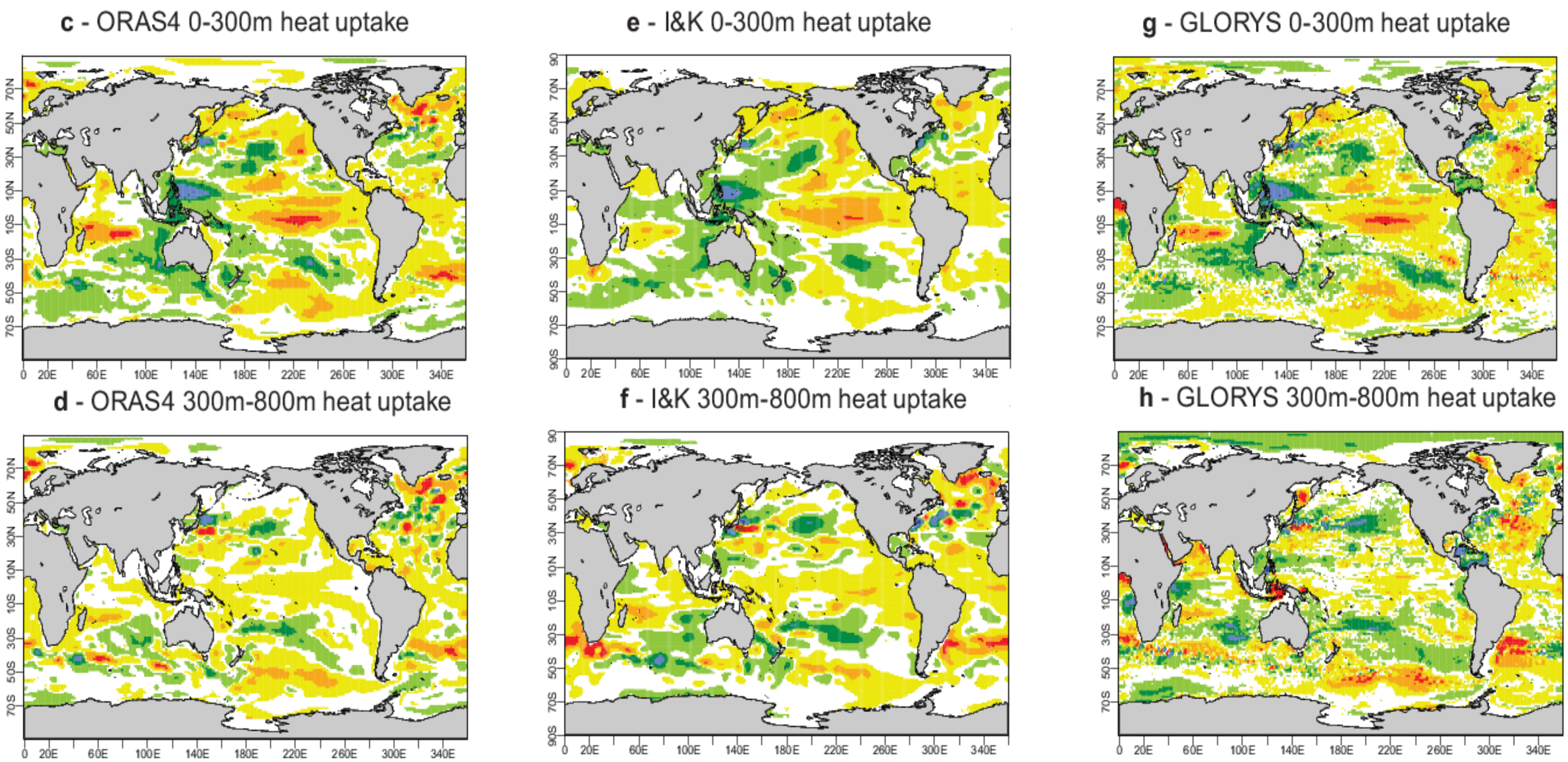
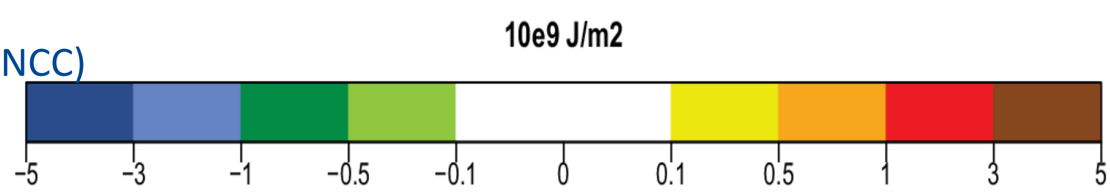
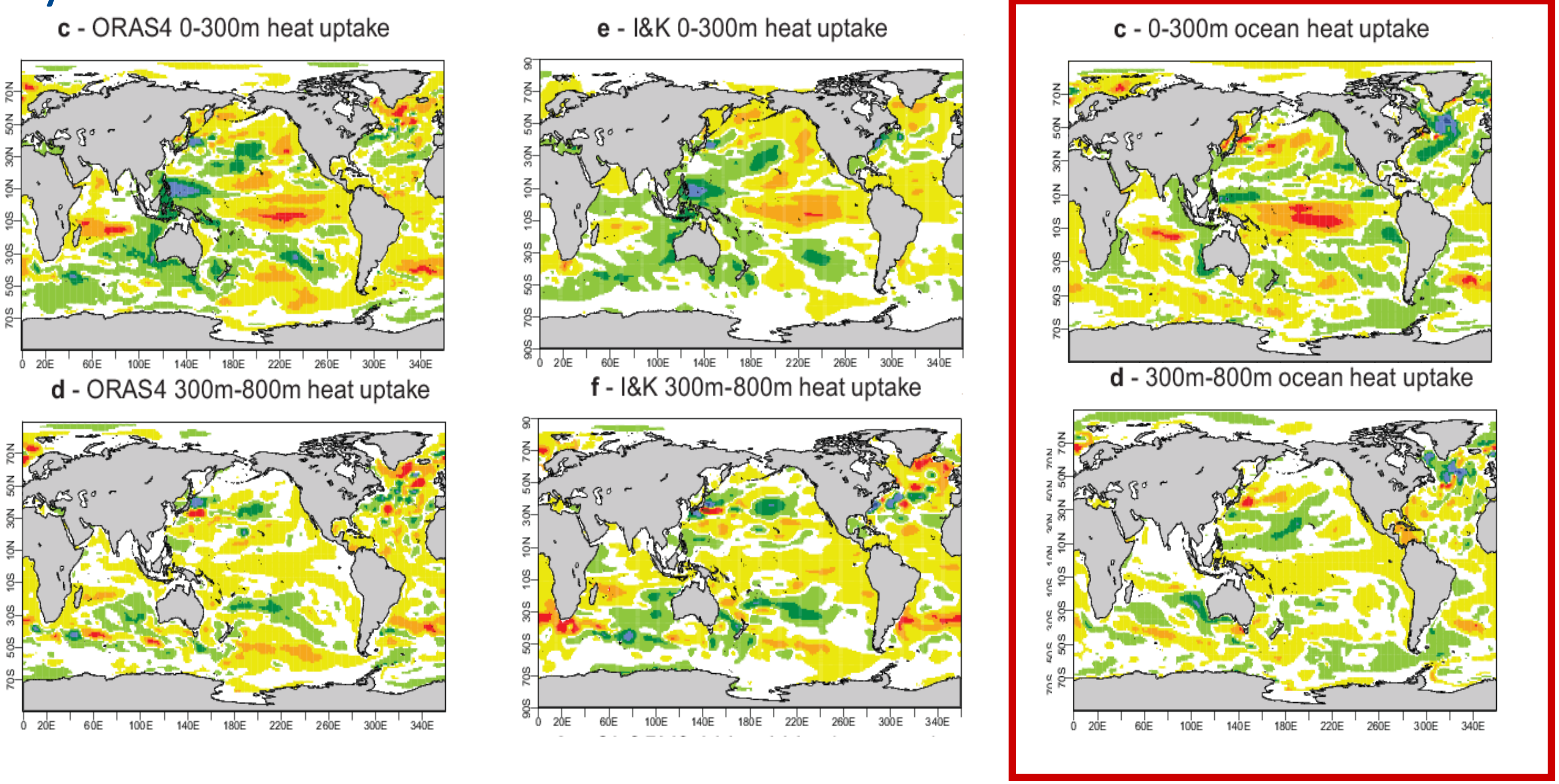


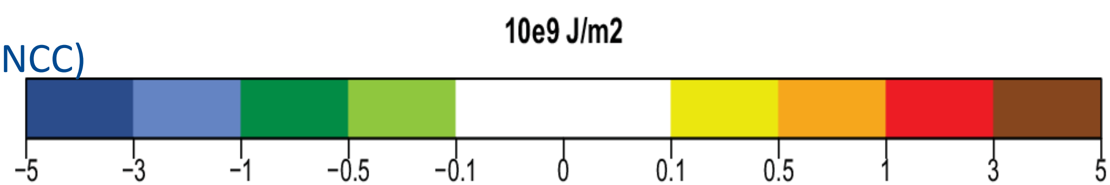
Guemas et al. (2013, NCC)



Ocean heat uptake computed as the average of the differences over the periods (2001-2005)-(1998-2000) from the ORAS4 ocean reanalysis.

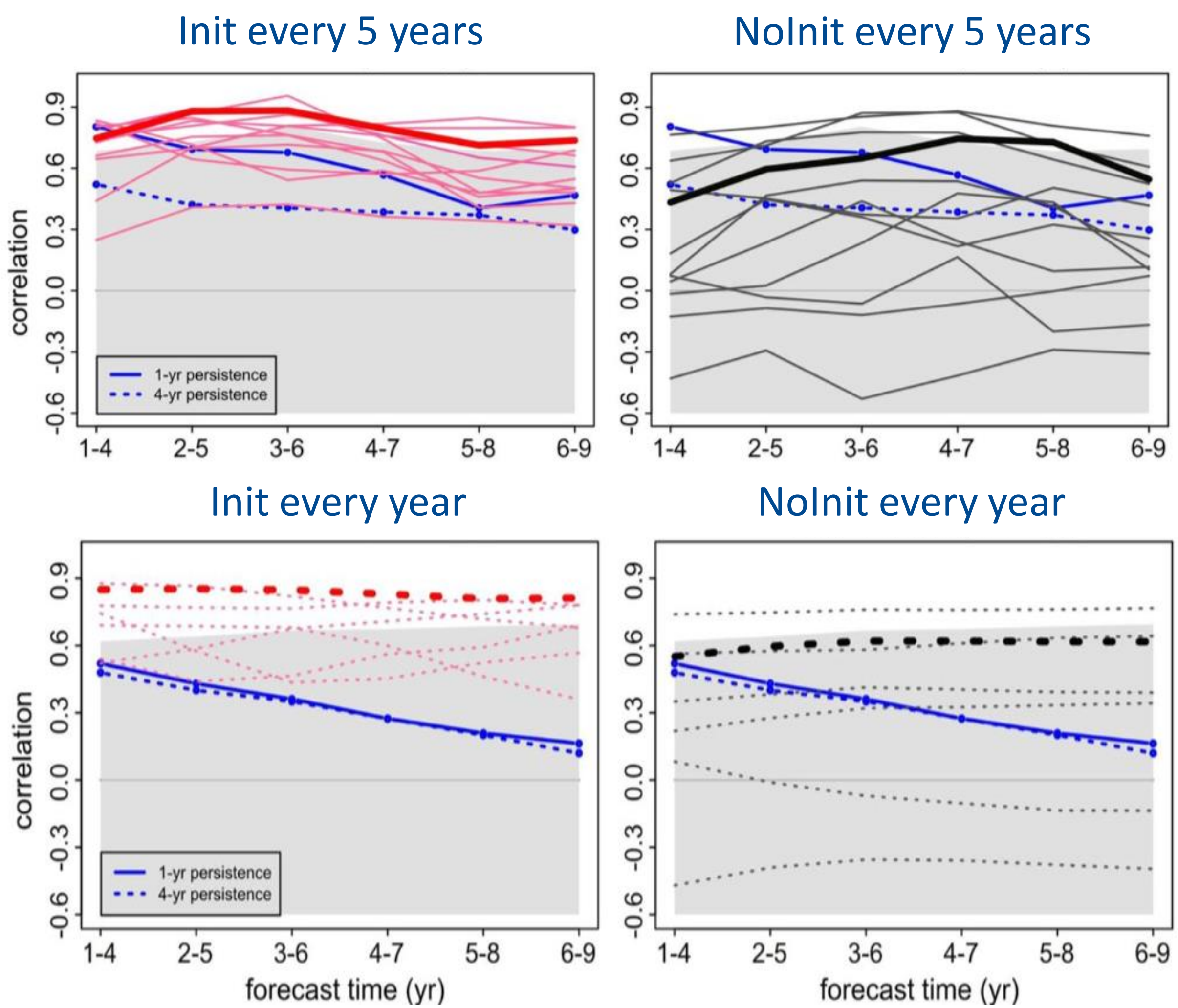


Guemas et al. (2013, NCC)



CMIP5 decadal predictions

Correlation of the ensemble mean of the AMV against GHCN/ERSST3b as a function of forecast time.

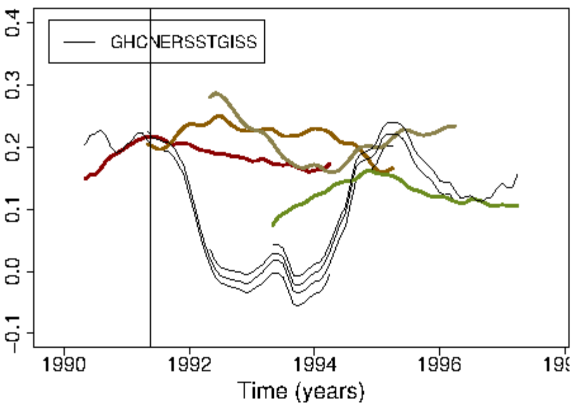


García-Serrano et al. (2014, Clim. Dyn.)

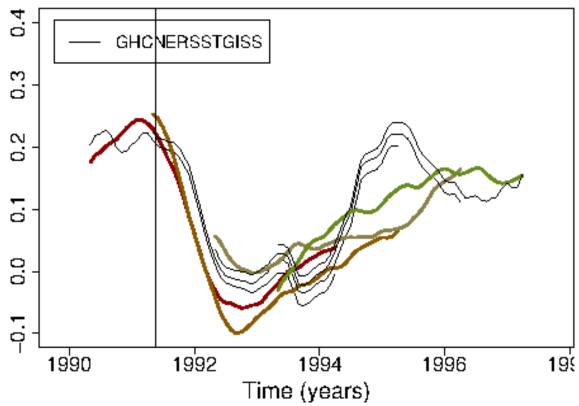
Post CMIP5: Volcanic aerosol

Global-mean surface temperature before and after the Pinatubo eruption simulated by EC-Earth 2.3 with five-member ensemble hindcasts. Observational data is a mix between GHCN, ERSST and GISS.

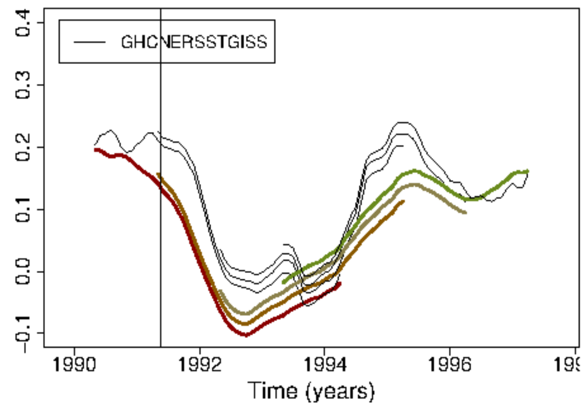
Both the initialisation and the volcanic forcing specification improve the simulations.



Initialisation and no volcanoes



Initialisation and volcanoes



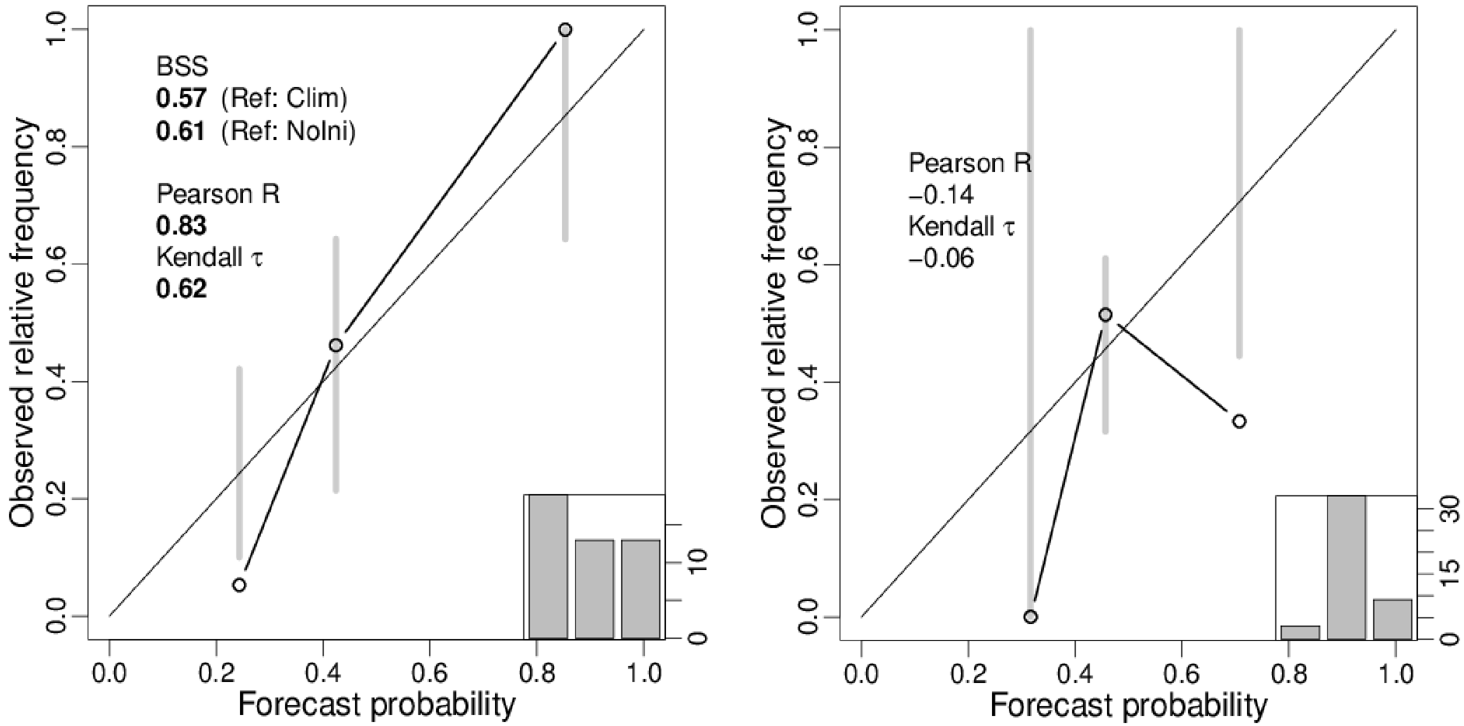
No initialisation and volcanoes

M. Ménégoz (IC3)

Service-driven decadal predictions

Reliability diagrams of (left) initialised and (right) uninitialised MME simulations for basin-wide **accumulated cyclone energy** (ACE). The results are for 2-9 year averages above the climatological median over 1961-2009. Statistically significant values are in bold.

Some of the added value of the predictions is their better management of uncertainty, which leads to increased **credibility**.



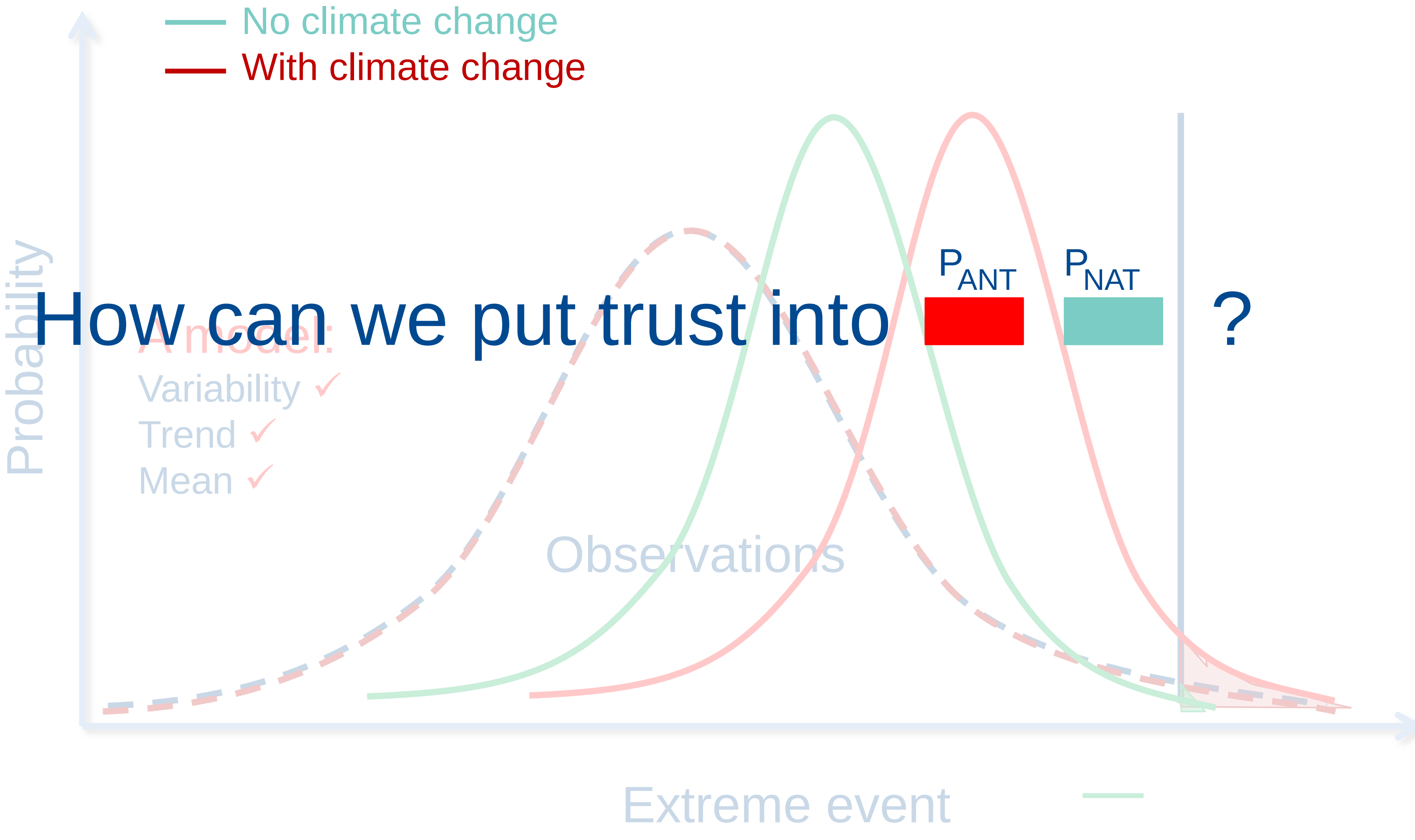
Caron et al. (2015, GRL)

Interpreting reliability

- Probability enables honest communication with end user and better decisions.
- Reliability: if the probability of an event y is q the event should happen on average q 100% of the times $P(y=1|p=q)=q$.
- The reliability diagram is a plot of $P(y=1|p)$ over p. Pointwise consistency bars by resampling and histogram of probabilities (sharpness diagram) should be added.
- The rank histogram verifies the raw ensemble, independent from the method used to obtain the probabilities, and measures whether the ensemble and the observation come from the same underlying distribution. It requires exchangeability and would benefit from testing for alternatives to flatness.

Event attribution and reliability

How can we put trust into P_{ANT} P_{NAT} ?



Event attribution and reliability

Simple system to create an actual and counterfactual model by setting a non-zero and zero value for *s*, respectively.

The beta parameter sets the reliability of the system and is set equally for both worlds (example with 1000 ensemble members and ratio between *s* and the residual variability of 1.5).

$$x_t = x'_t + st$$

$$x'_t \backsim N(0, \sigma_x = 1), t \in [0, T]$$

$$F_t = \alpha x'_t + \epsilon_\beta + st + (\epsilon_1, \ldots, \epsilon_M)$$

$$\epsilon_\beta \backsim N(0, \beta)$$

$$\epsilon_{1,\ldots,M} \backsim N(0, \sigma_M = \sqrt{(\sigma_x - \alpha^2 - \beta^2)}$$

s slope of the linear trend

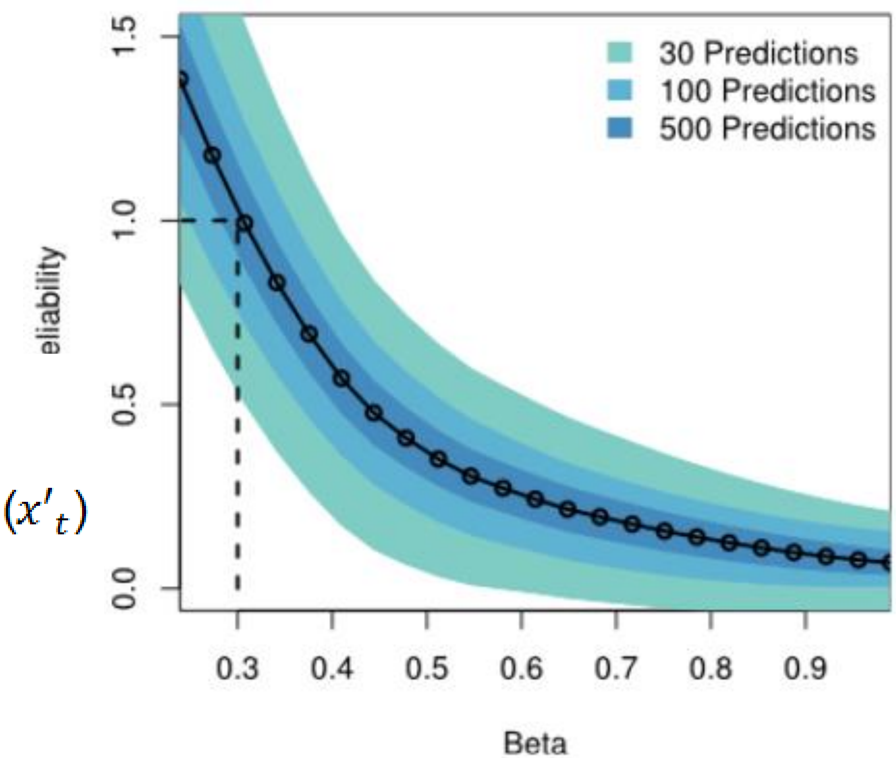
F_t synthetic forecast

α predictable fraction of the observed anomaly (x'_t)

β standard deviation of the forecast error (ϵ_β)

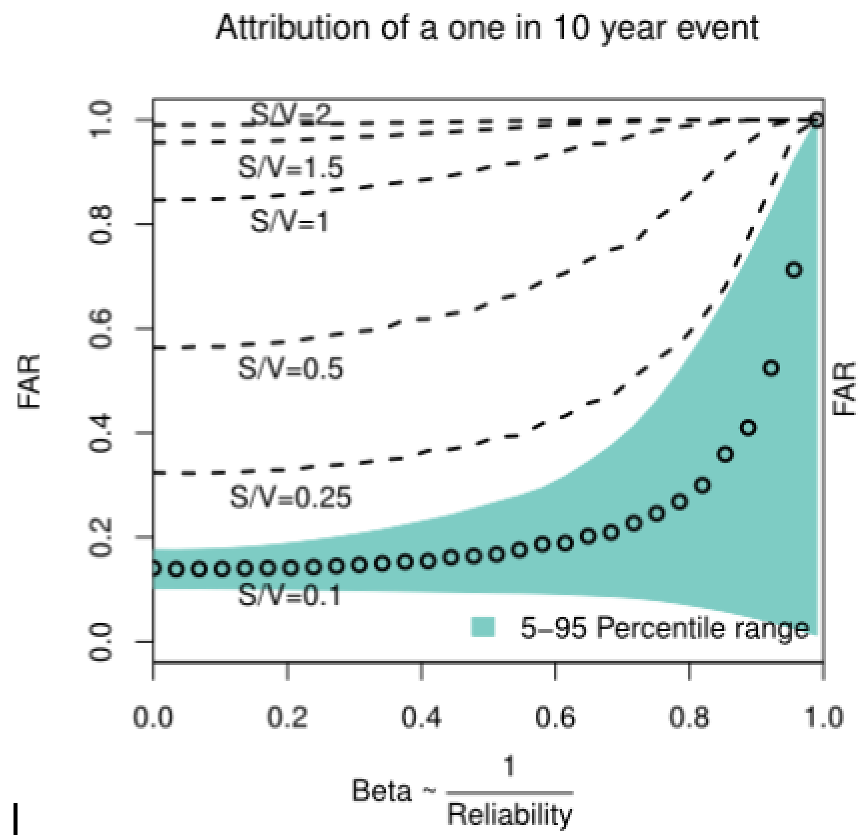
M ensemble size

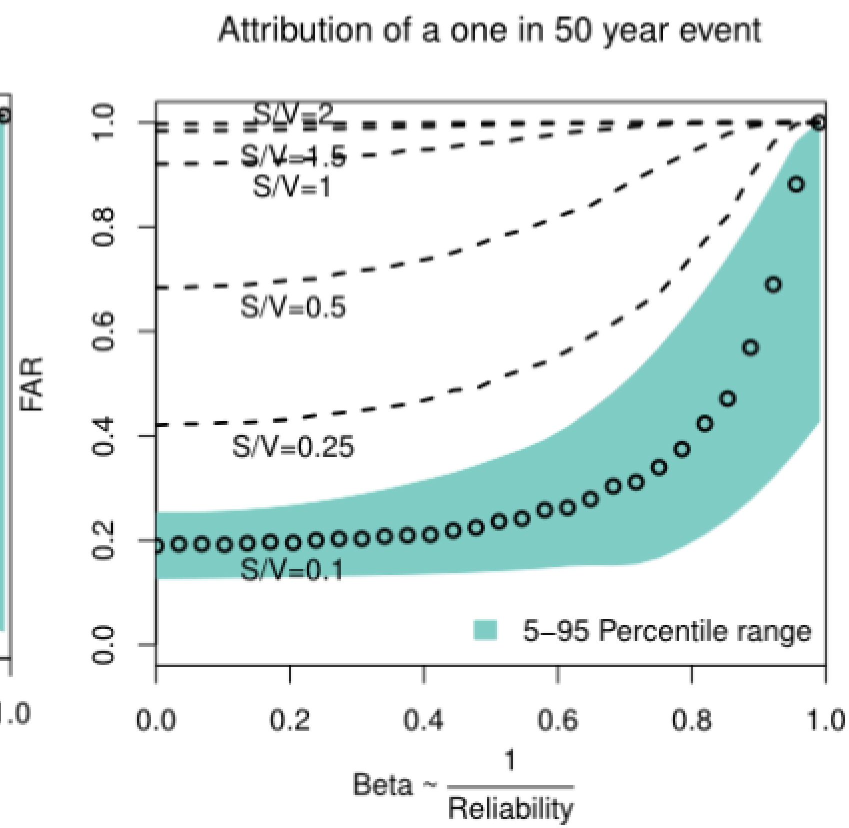
Bellprat and Doblas-Reyes (submitted)



Event attribution and reliability

Relationship between FAR and reliability. A positive bias exists in unreliable systems with low ratio of signal to interannual variability. There is also large uncertainty in the FAR values.





Bellprat and Doblas-Reyes (submitted)

More on users: Deciding now

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Bodegas Torres (a Spanish winery) is looking for new locations for its vineyards (and it's not the only one doing it).

Land is being purchased closer to the Pyrenees, at higher elevation. They are considering acquiring land in South America too, in areas where wine is currently not produced.

Bodegas Torres requests local climate information (including appropriate uncertainty assessments) for the vegetative cycle of the vine, which lasts 30-40 years.

Some users need to make the decision now.

Climate services is just a concept, predictions and projections are just a tool

Data analysis

S2dverification is an R package to verify seasonal to **decadal** forecasts by comparing experimental data with observational data. It allows analysing data available either locally or remotely. It can also be used online as the model runs.

s2dverification package

LOCAL STORAGE

ESGF NODE
or
OPeNDAP SERVER

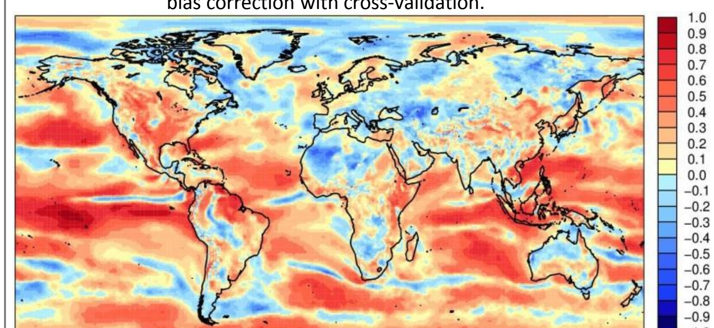
- Supports datasets stored locally or in ESGF (OPeNDAP) servers.
- Exploits multi-core capabilities
- Collects observational and experimental datasets stored in multiple conventions:
  - NetCDF3, NetCDF4
  - File per member, file per starting date, single file, …
  - Supports specific folder and file naming conventions.

BASIC STATISTICS

SCORES
Correlation, ACC, RMSSS, CRPS, ...

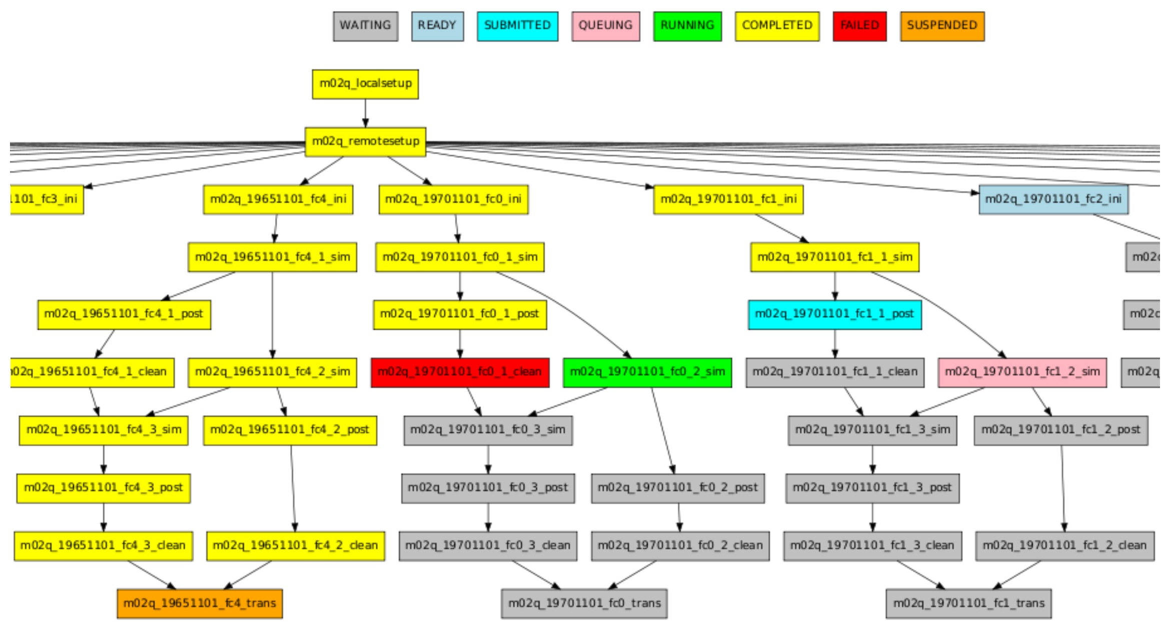
PLOTS

Anomaly Correlation Coefficient. 10M Wind Speed ECMWF S4 1 month lead with start dates once a year on first of November and Era-Interim in DJF from 1981 to 2011. Simple bias correction with cross-validation.



Infrastructure: Autosubmit

- **Automatisation:** Preparing and running, postprocessing and output transfer, all managed by Autosubmit. No user intervention needed.
- **Provenance:** Assigns unique identifiers to each experiment and stores information about model version, configuration options, etc
- **Failure tolerance:** Automatic retrials and ability to repeat tasks in case of corrupted or missing data.
- **Versatility:** Currently run EC-Earth. NEMO and NMMB models on several platforms.



Workflow of an experiment monitored with Autosubmit (yellow = completed, green = running, red = failed, …)

D. Manubens, J. Vegas (IC3)

Summary

- Requests for climate information for the next 30 years comes from a broadening range of users and should be addressed from a climate services perspective. What forecasters provide is still far from what some users demand (even in the absence of skill) and is only part of a complex story.
- Land-surface and sea-ice initialisation increases the forecast quality, including a range of extreme measures.
- Decadal prediction shows signs of providing useful information for some extreme events.
- Models still have substantial errors that need to be understood and communicated and have to deal with a substantial drift.
- FAR in unreliable systems (valid not just for forecast systems) with low signal-to-noise ratios should be used with care as could be biased and highly uncertain.
- Investment in infrastructure (hardware, software, people) is paramount to make progress.